

LIQUIDITY SHOCKS AND SEO UNDERPRICING

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ABSTRACT

We hypothesise that certain market conditions could lead to liquidity shocks that will consequently increase SEO underpricing (defined as the close-to-offer return). We propose three scenarios of market conditions, namely aggregate issues with large volume, large market declines and market volatility. Using a sample of about 5,000 seasoned equity offerings from 1987 to 2009, we found that market volatility is significantly and positively related to SEO underpricing after controlling for other factors.

We employed an estimation method proposed by Chambers and Dimson (2009) to examine the behaviour of SEO underpricing over our sample period from 1987 to 2009. We found that after controlling for changing risk composition, price practice, market conditions and the influence of underwriter reputation and analyst coverage, there was still an upward shift in SEO underpricing over the sample period, and the pattern cannot be fully explained by the practice of setting offer prices at lower integers.

We borrowed the investment banking power hypothesis from the literature and argued that the upward shift of SEO underpricing over the sample period could be explained by the increase of investment banking power. As the industry structure of underwriting transfers from a competitive market to an oligopoly market, banks use non-price dimensions to gain market power and consequently increase SEO underpricing.

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CHAPTER 1: INTRODUCTION

1.1. Research Questions

There are several ways a company can raise funds. These include taking loans from a commercial bank, issuing corporate bonds in the debt markets and issuing shares in the stock markets. A company's first public offering of shares is called an Initial Public Offering (IPO) and each subsequent offering is a seasoned equity offering (SEO) (Ross et al., 2006, p374). As a fund raising measure, the SEO has experienced substantial growth during the past two decades. Bortolotti et al. (2008) document the total volume of global SEOs in 1991 at \$91,904 million (in the equivalent of 2004 US dollars) and the number of issues at 1,099, increasing to \$320,714 million and 3,223 issues in 2004.

As the SEO has become an increasingly important mode of fund raising, SEO pricing models have naturally attracted more attention in the literature. A number of theoretical pricing models and empirical pricing models have been proposed, and accompanying the expansion of the SEO market, SEO underpricing has increased substantially – this is defined as the difference between the closing price prior to the offer (or the offer day closing price) and the offer price. Several studies have examined SEO underpricing in the long run and found that average SEO underpricing has increased from about 1% in the 1980s to about 3% in the 2000s (e.g. Corwin, 2003; Autore, 2011).

The title of this PhD study is *Liquidity Shocks and SEO Underpricing*, and it endeavours to join and contribute to the literature by addressing the following research questions:

1. Could liquidity shocks caused by certain market conditions increase SEO underpricing?
2. What is the behaviour of SEO underpricing over the long run and what is the reason behind the pattern?
3. What is the relationship between SEO flotation costs and liquidity of underlying shares?

1.2. Research Motivation and Proposed Contributions

Unlike IPO pricing, historical market data are available for SEO pricing. The offer price can be decided by making an adjustment on the closing price prior to the offer. In an SEO transaction, the offer price is often set lower than the closing price prior to the offer; in other words, the offering is often underpriced. The SEO underpricing can be defined as the close-to-offer return or offer-to-close return. The former is the percentage change from the prior closing price to the offer price while the latter is the percentage change from the closing price on the issue date to the offer price. In this thesis, we follow the definition by Corwin (2003) and refer to SEO underpricing as the close-to-offer return.

Studies in SEO underpricing not only borrow a number of hypotheses proposed in IPO underpricing but also propose some exclusive hypotheses for SEO underpricing¹. Several important determinants of SEO underpricing have already been identified. These determinants include offer characteristics and firm characteristics². Based on the price pressure hypothesis (Scholes, 1972; Corwin, 2003), we have developed a hypothesis that certain market conditions could lead to liquidity shocks that consequently increase SEO underpricing. We propose three proxies to represent three scenarios of market conditions, namely aggregate issues with large volume, large market declines and high market volatility. Therefore, the first contribution we plan to make in this study is to incorporate market conditions into the existing empirical models of SEO underpricing.

One significant phenomenon in the SEO market is the increase of SEO underpricing since the 1980s, which is documented in a number of studies (e.g. Altinkilic and Hansen, 2003; Corwin, 2003; Kim and Shin, 2004; Mola and Loughran, 2004; Autore, 2011). Several studies have already examined the pattern of SEO underpricing from the 1980s to the 2000s and proposed their own explanations for the pattern (e.g. Mola and Loughran, 2004; Kim and Shin, 2004; Autore, 2011).

Recently, Chambers and Dimson (2009) proposed an estimation method to examine the long run behaviour of IPO underpricing in the UK. Under their method, all variables except year dummies are demeaned, then the coefficients of the year dummies are estimated using a regression model. The year dummy coefficients

¹ For example, see Chemmanur and Jiao (2011).

² For the discussions of offer characteristics and firm characteristics, see e.g. Jeon and Ligon (2011).

represent the magnitude of SEO underpricing in a given year by an IPO with characteristics in line with average values for the sample.

The estimation method proposed by Chambers and Dimson (2009) controls for the effects of other factors and therefore presents a clear economic interpretation of the year dummy coefficients. To our best knowledge, this estimation method has not been employed in studies of SEO underpricing over the long run, so we fill the gap by employing this estimation method to examine the behaviour of SEO underpricing during our sample period from 1987 to 2009, which could be regarded as the second contribution of the study.

Setting SEO offer prices at next lower or other lower integers has become a common practice since the 1990s (e.g. Mola and Loughran, 2004; Jeon and Ligon, 2011; Huang and Zhang, 2011)³. To examine the effects of this practice on the behaviour of SEO underpricing over time, we divide our sample into two subsamples. One only includes offers that were priced at the next lower or other lower integer offer price. The other subsample includes the rest of the offers. If the patterns of annual underpricing dummies of the two subsamples are similar, we can conclude that setting offer prices at lower integers cannot fully explain the behaviour of SEO underpricing over time⁴.

There is some evidence suggesting that issues with more liquid shares have lower investment banking fees, *ceteris paribus* (Butler et al., 2005). Since both SEO

³ For instance, if the prior closing price of the issuer's stock is \$10.7, setting the offer price at next lower integer means that the offer price is set at \$10, and setting offer price at other lower integer means that the offer price is set at \$9, \$8, etc.

⁴ The annual underpricing dummies refer to the year dummy coefficients estimated by the method proposed by Chambers and Dimson (2009).

underwriting spreads and underpricing belong to flotation costs, we also check the relationship between liquidity of underlying shares and SEO flotation costs with our sample in Chapter Seven.

1.3. Thesis Structure

The thesis is structured as follows: in Chapter Two, we discuss the important elements of SEO transactions. This discussion provides background knowledge that is important for the sample selection and hypothesis development that follows. In Chapter Three, studies related to equity offerings are categorised, and we also discuss the studies related to liquidity shocks, liquidity and liquidity risk.

Chapter Four discusses sample selection and presents the descriptive statistics. Chapter Five analyses the current explanations for the increase in SEO underpricing. In Chapter Six we test the hypothesis that certain market conditions could cause liquidity shocks and consequently increase SEO underpricing. After that, we analyse the behaviour of SEO underpricing over the sample period using the estimation method proposed by Chambers and Dimson (2009). Chapter Seven examines the relationship between liquidity of underlying shares and flotation costs (including gross spread and SEO underpricing). Robustness tests are conducted in Chapter Eight. Conclusions are presented in Chapter Nine.

CHAPTER 2: INTRODUCTION OF SEASONED EQUITY OFFERINGS

In this chapter we discuss the definition of equity offerings and the differences between initial public offerings (IPOs) and seasoned equity offerings (SEOs). We then introduce the major types of flotation method, underlying shares and the role of investment banks. Last but not least, trends in seasoned equity offerings are discussed in a global context. The material discussed in this chapter is crucial for the sample selection and hypothesis development in the following chapters.

2.1. Introduction of Equity Offerings

Most companies at their birth raise equity from a small number of investors. If the investors want to sell their stakes, they generally find the market illiquid. Later, as the company develops and needs additional equity capital, it may become desirable to go public by selling shares to a larger number of investors (Ibbotson and Ritter, 1995). This process is called an Initial Public Offering (IPO). In order to complete the IPO, the company needs to hire auditing and law firms to prepare the required documents and investment banks to underwrite the offering. Thus, the IPO process generates auditing fees, legal fees and underwriting fees. In return, the company not only raises the funds it needs but also improves the liquidity of its shares. With the enhanced liquidity, the company can raise funds on more favourable terms than if it had to compensate investors for bearing the lack of liquidity before the IPO.

After the IPO all subsequent issuances of shares by the company are referred to as seasoned equity offerings (SEOs), also called follow-on offerings or secondary offerings in the industry. By one definition (Ross et al., 2006), a secondary equity offering is a registered offering of a large block of a security that has been previously issued to the public.

SEOs can be used to raise fresh equity capital for the firm or to reduce the positions of existing shareholders (Geddes, 2005). In the former case, the proceeds of the sale go to the issuing firm and the offerings are issued in the primary market. In the latter case, which is also called secondary distribution, existing shareholders wanting to reduce their positions in the shares of the firm are often large investors or institutions. Because the number of shares they want to sell is large, they use SEOs to sell the blocks in the secondary market, with the proceeds of the sale going (of course) to those shareholders rather than to the issuing company. An SEO can be issued in both the primary market and the secondary market simultaneously. In this case, both the issuing firm and the shareholders can receive the proceeds of the sale according to the proportions of shares that they hold. Because SEO studies emphasise financing activity, many studies in SEO underpricing select their samples with the constraint that the offerings should include at least some primary shares.

2.2. Main Differences between SEOs and IPOs

Although SEOs and IPOs follow similar processes, there are important differences between the two. One is the degree of information asymmetry, which is higher in IPOs than in SEOs, since IPOs involve the sale of shares in closely-held firms in which

some of the existing shareholders may possess non-public information (Ibbotson and Ritter, 1995). Conversely, SEOs are conducted by listed firms and their information is more accessible due to their status as public firms. For example, SEO issuers have the market closing price prior to the offer. According to the theory of market efficiency, this price would reflect all the information relating to the company if the market were efficient. This closing price prior to issue is used as the starting point for SEO pricing. In contrast, before an IPO there is no market price for the securities of the issuing firm.

Another difference is in flotation methods (also called underwriting method in some studies, since most SEOs are underwritten by investment banks). In the US, the firm commitment method is the main flotation method used in IPO transactions. According to the record of All US Public New Issues in SDC Platinum, the issues underwritten by the firm commitment method made up 98% of all US IPOs during the period from 1980 to 2010. For SEOs, although the firm commitment method is also the main type of underwriting method (Booth and Smith, 1986; Eckbo et al., 2007), issues underwritten by other flotation methods take a substantial portion of all offerings. For instance, from 1980 to 2010, the record of All US Public New Issues in SDC Platinum shows that around 82% of all US SEOs were underwritten by the firm commitment method and the rest of the offerings were underwritten by other flotation methods.

Last but not least, SEOs have a larger market than IPOs. For instance, in 2004-2005 the global SEO dollar volume was nearly double the IPO volume, and 2006's near record IPO volume of \$256.4 billion was still around 80% of global SEO issuance, which was \$317.2 billion (Bortolotti et al., 2008).

2.3. Flotation Methods, Underwriters and Types of Underlying Securities

As discussed in the previous section, there are differences in main flotation methods between IPOs and SEOs. In this section, we discuss six main flotation methods for equity offerings, namely firm commitment, best efforts, rights, accelerated underwriting methods, self-registered and private placements⁵.

2.3.1. Flotation Methods

Firm commitment: Under the firm commitment method, the underwriter will buy the issue from the issuing firms and guarantee sale of a certain number of shares to investors (Ross et al., 2006). The underwriter assumes all the risk through the guarantees and so underwriting fees with the firm commitment method are high. The detailed process of firm commitment is discussed in the next section.

Best efforts: In a best efforts transaction an investment bank only promises to sell as much of the issue as possible to the public but does not make a promise to sell a certain number of securities (Brealey et al., 2006). Under this flotation method, the investment banks assume less risk than in firm commitment issues and, consequently, charge relatively low underwriter fees. As noted in the previous section, the best efforts method is often used in IPOs and is rare in SEOs. This is probably because IPOs are riskier than SEOs because of the problem of information asymmetry: IPO stocks have no public market price prior to the issue, no stock analysts following the

⁵ We summarise these six flotation methods from different sources. Firm-commitment, best efforts and rights are based on Eckbo and Masulis (1995). Self-registered and private placement are based on Eckbo et al. (2007). Accelerated underwriting methods are based on Geddes (2005) and Bortolotti et al. (2008).

company, limited information available to the public and a high concentration of ownership, often with managers as the major holders of equity (Eckbo and Masulis, 1995). Therefore, investment banks choose the best efforts method if they believe the risk associated with the IPOs is too high.

Rights: A rights offer is quite different from a firm-commitment offer. A rights offer can be non-underwritten or underwritten (Eckbo et al., 2007). In the former case, the issuer assumes all the risk associated with the issue. The rights offer grants only existing shareholders the right to purchase a pro rata portion of a new equity issue at a fixed price (Eckbo and Masulis, 1995). In the US, a rights offer is often valid only within one month of the issue (Eckbo et al., 2007). During that time the shareholders have the right to accept or decline the offer. Therefore, a rights offer is like an option or a warrant. The shareholders can subscribe, sell the rights in the secondary market, or do nothing (Geddes, 2005). At the issue date the offer price is often set at a discount from the current market price. However, during the waiting time, the offer price might still exceed the market price, which ends in offer undersubscription or offer failure. The rights offer price is therefore often more discounted than that of a firm commitment offer. Typically the rights subscription price is 15-20% below the current market price of the stock (Eckbo and Masulis, 1995).

Because the current shareholders can capture the full value of rights either by exercising the rights or selling rights in the market, theoretically the firm can increase the offer price discount at no extra cost until the success of the issue is almost guaranteed. However, the above argument is not always the case, again because of the problem of information asymmetry (Eckbo and Masulis, 1995). If the rights are

unsubscribed, the issuing firm can either reallocate unsubscribed rights among subscribing shareholders or hire an underwriter to “stand by” to guarantee the proceeds on any unsubscribed rights (Eckbo et al., 2007).

The underwritten rights offer is often called a **Standby Rights Offer** (Eckbo and Masulis, 1995). In a standby rights offer, because the underwriters bear the price risk as they do in a firm commitment issue, they charge a fixed “standby” fee and “take-up” fee in the transaction (Eckbo et al., 2007). Eckbo and Masulis (1992) report that rights offers in the US market are usually fully subscribed. The portion taken by underwriters in a standby rights offer is typically around 15% of the issue (Singh, 1992). In the US market, rights issues are largely confined to closed-end investment companies. However, in Europe, seasoned equity issues must generally be sold by rights (Brealey et al., 2006)⁶.

Accelerated underwritings: Accelerated underwriting refers to the underwriting methods that execute the transactions much more quickly than traditional firm commitment underwriting. This concept was proposed by Bortolotti et al. (2008). According to Bortolotti et al. (2008), there are three forms of accelerated underwritings, namely accelerated book-built offerings, block trades and bought deals⁷.

Accelerated book-built offerings (ABOs) have a process similar to the traditional firm-commitment underwriting in terms of book-building, shares allocation and

⁶ Brealey et al. (2006, p402) also mention that companies in Europe have increasingly lobbied for the freedom to make general cash offers. Rights issues compose one quarter of total volume of SEOs in Europe according to Bortolotti et al. (2008).

⁷ Bortolotti et al. (2008) do not present the difference between block trades (BTs) and bought deals (BDs). Geddes (2005) suggests that BTs and BDs are the same type of flotation method.

responsibilities of underwriters. However, ABOs are executed much more rapidly than conventional firm commitment offers. Geddes (2005) suggests that ABO firms are generally reasonably well-known, with good share liquidity.

In both block trades (BTs) and bought deals (BDs), large blocks of shares are priced by auction. Geddes (2005) mentions that bought deals (BDs) are sometimes referred to as block trades (BTs). In other words, BTs and BDs are the same type of flotation method. The issuing firms sell the shares to an investment bank for the highest bid, then the banks resell the shares to institutional investors. During the process there is little information production. Therefore, both BTs and BDs are executed very rapidly.

The main advantage of accelerated underwriting is that it reduces the cost (SEO announcement reaction and underwriting fees) for the issuing firms (Bortolotti et al., 2008). In recent years, the growth of accelerated underwriting has challenged the domination of traditional underwriting. Armitage (2010) documents that in the UK much of the SEO issuance declined by existing shareholders is bought in a few large blocks by both other existing shareholders and new investors. He argues that the rise of block trades is the reason for the decline of rights issues in the UK. Moreover, seasoned common stock sales executed through accelerated underwritings now account for over half the value of US SEOs⁸. Figure A-1 in Appendix 1 to this chapter shows the evolution of global SEOs from 1991 to 2004. The number of ABOs increased rapidly from 1997 and ABOs accounted for almost one third of the total SEOs by 2004.

⁸ The results are based on the sample selection criteria of Bortolotti et al., 2008.

Shelf-registration: The US Securities and Exchange Commission introduced Rule 415 in 1983, allowing a single registration document to be filed that permits the issuance of multiple securities. In order to use this flotation method the issuer must meet four requirements: 1) common stock (with or without voting rights) having a market value of at least \$75 million; 2) the issuer has had no default on debt, preferred stock or rental payments for 3 years; 3) all SEC disclosure requirements have been met for the last 3 years; 4) the firm's debt is investment grade (Eckbo et al., 2007).

Issuers use shelf-registration to register securities that will be offered on an immediate, continuous or delayed basis over the next two years using a list of possible underwriters. Shelf-registration allows the issuing firms to execute issues when market conditions become favourable, thereby increasing the flexibility and the speed of the issue.

On December 1st, 2005, the SEC created a new category of issuers described as well-known, seasoned issuers (WKSIs). WKSIs must meet one of two conditions required by the SEC. WKSIs are given automatic shelf-registration status, which means their registration statements are automatically effective on filing without SEC review (Eckbo et al., 2007). It is worth mentioning that shelf-registration has become an important part of the SEO market in the US. Autore (2011) documents that \$51 billion was through 317 shelf offerings from 2004-2006, while only \$18 billion was raised via 146 traditional offerings during the same period in their sample⁹.

⁹ Their sample selection requires data from the Compustat database, which could screen off a number of small issues offered by traditional offerings.

Private placement: In a private placement the issuing firm sells the entire issue to a single investor or consortium of investors, bypassing current shareholders (Eckbo et al., 2007). These placements are non-public and the SEC has issued Rules 144 and 144a to regulate private placements in the US. Private placement is the simplest way for a foreign firm to issue equity in the US. An issuer is not required to prepare a registration statement and changes in accounting to meet US GAAP, and the reporting requirement for an issuer is limited to that which is required in the issuer's home market (Geddes, 2005). Although the threshold for a foreign issuer is low, placements are subject to a number of regulations (such as the Securities Act of 1993) designed to protect investors. For private placements, typical investors are institutions such as banks, insurance companies and pension funds.

2.3.2. Underwriters and Syndicates

Underwriters (investment banks) act as the agents in the transactions, executing the issue for their clients, the issuing firms. Among different underwriting methods, underwriters play a crucial role in firm commitment issues. In a firm commitment issue, underwriters: 1) provide issuers with procedural and financial advice; 2) promise to buy the entire issue from the issuing firm; 3) then resell the shares to investors (Brealey et al., 2006).

In order to spread the risk associated with the issue, underwriters often form a syndicate to distribute the shares (Eckbo et al., 2007). Geddes (2005) suggests that the syndicate is formed to broaden distribution, to encourage research support and market-

making following the offering and due to reciprocity¹⁰. Within the syndicate, banks are categorised into different groups according to their roles and responsibilities in the transactions and according to whether they are receiving management fees, underwriting fees, selling concessions and reallowance fees¹¹. The sum of these fees is called gross spread (also called total management fees in SDC Platinum), represented as a percentage of the proceeds.

Book managers: Book managers (also called lead managers or lead underwriters) are the investment banks that form and coordinate syndicates and receive the management fees¹². In SEO transactions, the book managers maintain a record of activity for the syndicate and underwrite the largest portion of the securities¹³. Many studies of IPOs and SEOs recognise the important role of book managers. Loughran and Ritter (2004) use the ranking of lead managers to represent the reputation of the underwriter in IPOs. Studies of SEOs likewise use a similar ranking and some studies have found that SEOs underwritten by lead managers with high reputations are less underpriced than others (Mola and Loughran, 2004; Kim and Shin, 2004). Mola and Loughran (2004) additionally used the ranking of lead managers' analyst teams to represent the analysis capacity of the underwriters.

Co-managers: Co-managers (also called co-lead managers or co-lead underwriters) do not keep the record of activity and, therefore, receive no management fees. They

¹⁰ Reciprocity means that banks invite other banks into the syndicate so that they can be invited into a new syndicate led by other banks next time.

¹¹ These terminologies (management fees, underwriting fees, selling concessions and reallowance fees) are taken from Thomson SDC Platinum.

¹² Book managers, co-managers and all managers are the terms used by SDC Platinum. All managers include book managers, co-managers and other syndicate members.

¹³ The role of book managers is stated in SDC Platinum.

underwrite lesser portions of the shares than book managers, though they share underwriting risks and underwriting fees with the book managers. Jeon and Ligon (2011) document that about 86% of syndicates in SEOs for industrial firms included more than one co-manager during the period 1997-2007, and the average number of co-managers was 2.44 per offering. Chen and Ritter (2000) and Corwin and Schultz (2005) found that more co-managers leads to more analyst coverage for issuers after IPOs. Corwin and Schultz (2005) also show that more co-managers results in additional market makers after the IPO is launched. Although issuers benefit from the increase in co-managers in the syndicate, Corwin and Schultz (2005) point out several factors that could limit syndicate size: offer size, competition for future underwriting business and the increase in underwriting spread for small IPOs.

Other Syndicate Members: Besides lead managers and co-managers, there are some banks which are only responsible for distribution of the shares (Eckbo et al., 2007). Selling concessions are allocated to all members in the syndicate, including lead managers, co-managers and other members. Reallowance fees are fees paid to secondary sellers (other members of the syndicate) of the securities¹⁴. Lead underwriters, co-managers and other syndicate members often commit to producing analyst coverage for the shares for a period after the offering, which is likely to draw the attention of investors for the securities and improve the stock's liquidity (Eckbo et al., 2007).

¹⁴ The definitions of selling concessions and reallowance fees are stated in SDC Platinum.

2.3.3. Types of Underlying Securities

There are many types of securities in SEO transactions¹⁵. Issuing firms may have different equity structures and different types of shares depending on their specific corporate charter. Some types of securities are excluded in many SEO studies due to the unique characteristics of the securities and so next we shall consider the various types.

The most common types of securities in SEOs are the common shares, class A shares, and class B shares¹⁶. Common shares (also called ordinary shares) are standard voting shares which give the holders the right to vote on matters of corporate policy and the composition of the board of directors (Ross et al., 2006). Class A (B) shares typically have enhanced (limited) voting rights or other benefits compared to the other types of shares in the firm (Brealey et al., 2006). Besides those shares, three forms of securities in SEOs are recorded by SDC Platinum and we discuss these next.

ADRs: In the US, foreign firms can issue American Depositary Receipts (ADRs) to raise capital. An ADR is a certificate representing ownership of shares of the foreign company, allowing that stock to be traded in the United States (Ross et al., 2006). Under the ADR arrangement, shares of the foreign company are deposited with a US bank. The US depository bank in turn issues ADRs in the name of the foreign company and also converts dividends and other payments into US dollars to ADR

¹⁵The types of securities discussed in this section are based on both the existing SEO studies (e.g. Corwin 2003; Kim and Shin, 2004; Mola and Loughran 2004) and the Types of Security in SDC Platinum.

¹⁶For SEOs, these three types of shares are the most common in SDC Platinum. There are also other uncommon types of stocks in SEOs, such as “Class A Limited Voting Common”, “Class A Sub Voting Common”, “Class C Shares”, “Class D Shares”, “Class E Shares”, “Class H Ordinary shares”, etc.

holders in the US (Diro Ejara and Ghosh, 2004). Due to the differences between operational environments, many studies in SEO underpricing exclude the non-US companies in their samples. Chen et al. (2009) present a study on how investment banks determined the gross spread paid by ADRs during the period 1980-2004. In their study, ADR SEO gross spread can be explained in a similar way (offer characteristics) to that explaining the gross spreads of US SEOs.

Unit: A unit is a merger of two or more classes of securities into a single securities product. Units are issued by unit investment trusts. A unit investment trust offers redeemable “units” to investors for a specific period. A unit represents one share of a fixed, unmanaged portfolio, generally of shares and bonds. A unit is designed to provide capital appreciation and dividend income. Three types of investment companies are unit investment trusts, mutual funds and closed-end funds (Fabozzi and Modigliani, 2003). Due to their complex features, units are often excluded from the sample selection in SEO underpricing studies.

REITs: REIT stands for real estate investment trusts. REITs are closed-end investment companies that invest in commercial real estate (Brealey et al., 2006). In SEO studies the term REITs refers to the shares issued by real estate investment trusts. These shares are traded on a stock market, therefore REITs are more liquid than direct investment in real estate. Real estate investment trusts invest in various types of real estate, diversifying the risks within the real estate industry. By aggregating individual investors, REITs provide investors easy access to real estate and diversification within real estate.

Based on the type of investment, REITs can be categorised into mortgage REITs and equity REITs (e.g. Lee and Chiang, 2004). Mortgage REITs that primarily invest in mortgages are akin to a bond investment, while equity REITs which invest primarily in commercial or residential properties using leverage are more akin to an investment in leveraged equity real estate. Because REITs are a closed-end investment vehicle in real estate, studies in SEOs often exclude REITs from their samples.

2.4. The Process of Firm Commitment Underwritten SEOs

As discussed in the previous section, firm commitment underwriting is the most prominent underwriting method in seasoned equity offerings. Understanding the process of firm commitment underwritten SEOs is crucial for hypothesis development in SEO studies. According to the timeline in a firm commitment offering, we divide the process into three stages, namely before the announcement, after the announcement but before the issue and after the issue.

Before the announcement: If the management of a firm wants to issue a seasoned equity offering, it first needs the approval of its board of directors. For most companies, shareholders authorise large numbers of shares far in advance of their possible use (Eckbo et al., 2007). Following approval, the issuing firm chooses one or more underwriters as lead underwriters. Lead underwriters then give advice on issuing items, such as price, the timing and size of the offering, road show mechanism, legal requirements, etc., then lead underwriters choose other banks to form a syndicate. The compensation mechanism is also negotiated within the syndicate. After the syndicate is formed, underwriters conduct a due diligence investigation to collect the

information about the issuing firm required to meet SEC filing requirements. With the help of underwriters, the issuing firm produces a prospectus and uses it to register the offering at SEC (Geddes, 2005).

Before the issue: Following announcement of the issue, the underwriters and the issuing firm managers travel to major cities to meet potential investors to discuss the planned offering. This process is called a road show (Geddes, 2005; Eckbo et al., 2007). Then the underwriters begin the book building process and collect bid information from institutional investors. This information is used to set the offer price. When the book building process is finished, the underwriters negotiate the offer price with the issuing firm. The underwriters usually sign an underwriting agreement to purchase the shares at a fixed price within 24 hours of the start of the offering (Eckbo et al., 2007).

Generally, the issue is oversold by the syndicate because the orders made by investors are not legally binding and can be withdrawn. If the issue is oversubscribed by investors, the allocation of shares can be either discretionary or non-discretionary. In a discretionary allocation, the issuer and underwriters determine who is allowed to buy and how much of their order is filled (Geddes, 2005). On the offering date, the underwriters confirm investors' orders and deliver shares to investors according to the allocation they made.

After the issue: When the offering is completed, there are still some responsibilities for underwriters. Underwriters in the syndicate often commit to providing analyst coverage for the shares for a certain period after the offering (e.g. Corwin and Schultz,

2005; Chen and Ritter, 2000). This practice can attract more market attention toward the shares of the issuing firm. Besides the analyst coverage, lead underwriters and co-lead underwriters have more responsibilities than other underwriters in terms of market-making commitment and price support. The market-making commitment requires lead underwriters to be active market-makers in the stock for a certain period after the offering (e.g. Corwin and Schultz, 2005). Price support means that lead underwriters can place limit orders to buy shares immediately after an offering without being subject to price manipulation restrictions (Eckbo et al., 2007).

If the offering is oversold, lead underwriters can buy shares either from the secondary market or from the issuers to meet the order. When the price in the secondary market drops below the offer price, lead underwriters buy shares in the secondary market. This practice will have the effect of supporting the price in the secondary market. If the price in the secondary market is above the offer price, there is no need for price support activity. Many contracts contain a Green Shoe Provision (Ross et al., 2006). This provision allows underwriters to exercise their over-allotment option to buy additional shares from the issuer and resell the shares to the public immediately when the price in the market is above the offer price.

2.5. The Trend of Global Seasoned Equity Offerings

In the global context, seasoned equity offerings are different between regions in terms of volume and underwriting methods. Bortolotti et al. (2008) summarise several points worth mentioning. Firstly, the volume of seasoned equity offerings worldwide rose substantially during their research period 1991-2004. For example, in 1991 the volume

of global SEOs was \$91 billion in 2004 terms and this figure increased threefold to \$320 billion by 2004. The number of global SEOs also increased from 1099 in 1991 to 3223 in 2004. The increase in both volume and transaction numbers suggests the increasing importance of SEOs as a way of financing around the globe. As a result, research into SEOs has more practical meaning and can make an increasing contribution to the broad area of corporate finance.

Secondly, the US market is the largest single-country SEO market in the world. During their research period, the volume raised in the US market reached \$8.27 billion, representing one quarter of the total volume raised in the world. The average proceeds in the US. during the period were \$115 million, while the average proceeds in Europe were only slightly higher at \$127 million. Both figures are significantly higher than the average size of the rest of the world. During the same period, although the total value of SEOs in the rest of world was \$14.4 billion, the average size was only \$61 million. These figures suggest that the US market is not only the most important single-country SEO market in the world, but also that it is leading the trend of global SEO. Therefore, research focusing on the US market can represent the latest trends in SEO markets and provide important implications for SEO transactions around the world.

Thirdly, Different regions have their own different prominent underwriting methods. In the US, the most prominent method is the firm commitment underwriting method. According to the figures provided by Bortolotti et al. (2008), during 1991-2004 firm commitment comprised around 75% of all SEOs in the US. This result is consistent with the findings of Eckbo and Masulis (1995), who report that 81.5% of all SEOs

during 1977-1982 were underwritten by firm commitment. In Europe, in contrast, only 3.8% of all SEOs were firm commitment offers during 1991-2004 (Bortolotti et al., 2008).

According to the statistics in Bortolotti et al. (2008), the majority of SEOs in Europe are accelerated transactions, placement offers and rights offerings. These three methods have a similar total value and number of transactions. In particular, the number of accelerated transactions represent one quarter of the number of all offers, while the total value of accelerated transactions consists of more than 30% of the total value of all offers. These statistics show that accelerated transactions are more prominent in Europe than in the US. In the rest of the world, firm commitment offers, placement offers and rights offerings have similar numbers of transactions, but firm commitment offers have the highest total value, representing 36.5% of total value of all SEOs. Thus, firm commitment offers are the main method in the rest of the world.

Although there are some differences between the US and the rest of the world, the US market remains the world's most important market for SEO transactions in terms of both total value and transaction numbers. As for underwriters, most of the top investment banks are US companies. According to the ranking made by the Financial Times as shown in Table A-1 in Appendix 2, in 2010 five of the top ten investment banks (in terms of fees) were US-oriented. Moreover, in the US market, almost all major underwriting methods have substantial proportions of total value and transaction numbers. Again, therefore, studies on the US market can provide indications not only for the US market itself but also for the rest of the world. Based on the above discussions, we next focus on US SEOs in this thesis.

CHAPTER 3: LITERATURE REVIEW

In this chapter several research topics related to SEOs are introduced. We discuss the reasons why firms might decide to issue seasoned equity. Studies related to SEO flotation cost are discussed in the second section of particular interest are the possible reasons for the increase in SEO underpricing. All the possible determinants about SEO underpricing are then discussed. Last but not least, this thesis focuses on the explanations involving liquidity shocks and liquidity risk. These discussions distinguish several concepts related to liquidity and pave the path for hypothesis development in the later empirical chapters.

3.1. Introduction of Studies on Seasoned Equity Offerings

As noted in Chapter Two, SEOs share a number of similarities with IPOs and, therefore, there are several common topics for both IPO and SEO studies. These topics are reasons for issue underpricing, market timing and flotation costs. SEOs also have unique features in underwriting methods, market price and more available public information. Those features involve SEO announcement effects, determinants for flotation costs, market microstructure effects of SEOs, the reason for choosing different underwriting methods and the reasons for the difference in prominent underwriting methods among regions, etc. In this section several important studies related to SEOs are introduced (briefly) to provide an overall picture of SEO research.

In SEOs flotation costs are an economically important portion of gross proceeds, where these include direct and indirect costs (Eckbo et al., 2007). Direct flotation costs refer to the costs directly associated with the issue, including fees paid to underwriters, registration and listing fees, legal fees, accounting fees and costs such as printing expenses. In IPO and SEO studies underwriting fees comprise the major portion of direct flotation costs. Studies on direct flotation costs are discussed in Section 3.2. Indirect flotation costs include three components, namely underpricing, announcement effects and the probability of issue withdrawal.

For IPO studies indirect flotation costs do not include announcement effects because the shares are not publicly traded before the IPO. Section 3.3 therefore only discusses studies on announcement effects and the probability of issue withdrawal. In Section 3.4 we discuss which factors may be attributed to a firm's decision to launch an SEO. Underpricing is the main part of this chapter and studies on SEO underpricing are discussed in Section 3.5 and Section 3.6. We further extend price pressure – one of the determinants of SEO underpricing to liquidity shocks and discuss the differences among liquidity, liquidity risks and liquidity shocks in Section 3.7. Last but not least, we discuss an option-based model in Section 3.8 and discuss the possibility of applying it to calculate SEO immediacy cost.

3.2. Studies on Direct Flotation Costs

In this section, we discuss two theories that emphasise the role of scale in deciding underwriting spread, namely economy of scale and u-shaped underwriting spread. We

then focus on the 7% solution and net proceeds maximisation theory. Last but not least, we discuss the effects of liquidity and information asymmetry on underwriting spread.

3.2.1. Economy of Scale and U-Shaped Underwriting Spread

For direct flotation costs, Smith (1977) examined mean underwriter fees and other expense of IPOs and SEOs across issue size categories and three major underwriting methods (firm commitment, best efforts and rights offers). Two findings are documented in his study. First, the issue size is negatively related to the underwriter fees as a percentage of gross proceeds. This relation is explained by the economy scale. Bigger economies of scale can lead to more efficiency of fixed costs and lower underwriting costs. Second, different underwriting methods affect the underwriting spread. Specifically, firm commitment offers have the highest mean underwriting spread while right offers have the lowest mean underwriting spread for comparable size offers.

As discussed in Chapter Two, firm commitment underwriting dominates SEOs and the majority of studies restrict their samples to firm commitment offers. The impacts of underwriting methods are not important for SEOs. Lee et al. (1996) conducted a study on direct flotation costs (including underwriting spread and other expenses) of IPOs, SEOs and convertible and straight corporate debt issues during the sample period 1990-1994. In their research direct costs average 7.1% for seasoned equity offerings and direct costs of SEOs exhibit economies of scale, which is consistent with the findings of Smith (1977).

However, underwriting spreads do not always fall as more capital is raised. After examining spreads on 1,325 SEOs from 1990 to 1997 in the US market, Altinkiliç and Hansen (2000) estimate that fixed cost is no more than 10% of total fees on average. In other words, underwriter costs are mostly variable. Also, their research indicates that issuers face U-shaped spreads. Initially the spread declines as the fixed cost is distributed over the proceeds, but as more capital is raised beyond a certain amount the underwriting spread will increase due to diseconomies of scale and the increase in variable costs. This nonlinear and U-shaped relationship is also confirmed by Hansen (2001), Drucker and Puri (2005) and Kim et al. (2010).

Two recent studies provide empirical evidence consistent with the explanations of economy of scale. Lee and Masulis (2009) employed a sample of 963 SEOs over the period 1990-2002 and found that the log of net proceeds is negatively related to gross spreads in their regression tests. Using a sample of 2071 SEOs from 1997 to 2007, Jeon and Ligon (2011) employed gross proceeds as a control variable and found the generally negative effect of gross proceeds on underwriting spread.

3.2.2. The 7% Solution and Net Proceeds Maximisation Theory

Chen and Ritter (2000) document that from 1995 to 1998, more than 90% of the 1111 IPOs raising \$20-80 million had spreads of exactly 7%, but only 26% of moderate size IPOs in the 1985 to 1987 period had 7% spreads. They call this clustering of spreads at 7% the 7% solution. The explanation for this large clustering of spreads is that investment bankers tend to use non-price competitions such as analyst coverage and price support to attract deals. The empirical tests of Hansen (2001) found no evidence

that investment bankers collude to profit from the 7% solution. Instead, Hansen (2001) argues that a 7% gross spread is an efficient contract since the 7% spread is not abnormally profitable.

Garner and Marshall (2010) employed a sample of 2265 firm commitment IPOs between 1993 and 2004. They document that more than a third of IPOs in their sample charged non 7% spreads. For those IPOs where underwriters (primarily middle-tier) charged something other than 7% and less than expected, they found evidence of a trade-off between IPO compensation and future SEO business. Chen et al. (2009) document the clustering of spreads at the 7% level for their American Depositary Receipt (ADR) IPO sample from 1980 to 2004, but no discernible clustering at any level was found in their ADR SEO sample and matched SEO sample during the same period. Moreover, they found that US underwriters set gross spreads differently for IPOs than SEOs.

Different to studies of the 7% solution, Yeoman (2001) developed the net proceeds maximisation theory to explain how spread and offering price are determined in all underwritten offerings (including IPOs and SEOs). In the study, both optimal spread and offering price for equity offerings were generated by equilibrium constraints, then the optimal spreads were tested with the sample of 1143 seasoned equity offerings from 1988 to 1993¹⁷. The empirical results are consistent with the implication of the net proceeds maximisation theory.

¹⁷ The optimal spreads for IPOs cannot be tested because the price uncertainty which is an input for the optimal spreads is not observable in unseasoned offerings.

The net proceeds maximisation theory suggests a potential trade-off or substitution relationship between underwriting spread and equity underpricing. But Garner and Marshall (2010) found no evidence that underwriters trade-off IPO compensation with underpricing when underwriters charge less than expected. Moreover, Kim et al. (2010) summarise three possible relationships between SEO underwriting spread and underpricing, namely insignificant relationship, substitution relationship (Yeoman, 2001) and complementary relationship. Kim et al. (2010) recognise the potential joint determination of underwriting spreads and initial returns. Their sample includes 4875 IPOs and 4348 SEOs from 1980 to 2000. Using a 3LS approach, the study confirms that underwriting spreads and underpricing were positively and significantly related for both IPOs and SEOs, which is consistent with the complementary relationship.

3.2.3. Liquidity, Asymmetric Information and Underwriting Spread

Butler et al. (2005) propose that stock market liquidity is an important determinant of the costs of raising external capital. This hypothesis is based on the idea that investment banks play a market making role in placing a seasoned offering and firms that have stocks with better market liquidity pay significantly lower underwriting spread. In the study, they used a sample of 2,387 SEOs from 1993 to 2000 to test the hypothesis that total investment banks' fees (gross spread) are substantially lower for firms with more liquid stocks.

In their sample they document substantial cross-sectional variation in SEO gross spreads and a set of liquidity variables is incorporated into regression. To control the effects of other factors, the study uses lead manager reputation (Megginson and Weiss,

1991), return volatility, share price, firm size, principal amount (Lee et al., 1996) and several dummy variables as control variables. The results show that firms with higher stock market liquidity have lower gross spread. Moreover, after setting the size quintile, the study found that the effect of liquidity is stronger for large equity issues, indicating that the marginal cost of illiquidity is higher for large issues.

Bid-ask spread used by Butler et al. (2005) could also be used as a proxy of asymmetric information (e.g. Corwin, 2003). Lee and Masulis (2009) emphasise the role of asymmetric information in determining underwriting spreads. However, the study points out that common measures used in the literature, such as stock return volatility (e.g. Altinkiliç and Hansen, 2000; Corwin, 2003; Drucker and Puri, 2005), analysts' earnings forecast dispersion (Marquardt and Wiedman, 1998), debt ratings (Liu and Malatesta, 2005) and bid-ask spread (Corwin, 2003) cannot provide strong theoretical support to reflect the information asymmetry between issuers and outside investors. Specifically, Lee and Masulis (2009) argue that these measures are likely to capture other economic effects beyond asymmetric information.

To solve the problem Lee and Masulis (2009) introduce accounting information quality as an alternative measure of information asymmetry. The hypothesis is that accounting statements are the primary source of information about corporate performance available to outside investors; if the accounting quality deteriorates, the investors' uncertainty about the firm should rise and demand for its equity should fall, leading to more underwriting efforts and thereby higher underwriting spread.

In their study, the measures of accrual quality which represent the accounting quality were generated by two models, namely the MDD (McNichols, 2002) and the FDD models. The underlying idea is to calculate the standard deviation of a firm's cross-sectional regression residuals across the period. Larger standard deviations of residuals mean a greater portion of current accruals left unexplained by the models, which suggests lower accrual quality. The regression results suggest that both measures have a significantly positive relation with gross spreads in their sample.

Besides accounting quality, recently Jeon and Ligon (2011) proposed the hypothesis that the co-managers in the syndicate can reduce the underwriting spread. Their study extends the research of the role of co-managers on the flotation costs from IPOs (e.g. Corwin and Schultz, 2005) to SEOs. The underlying notion is that highly prestigious banks tend to enhance the quality of the certification of the issues, reduce information asymmetry and, therefore, lower SEO flotation costs (Carter and Manaster, 1990; Habib and Ljungqvist, 2001; Megginson and Weiss, 1991).

The sample from Jeon and Ligon (2011) includes 2071 completed and 183 withdrawn SEOs from 1997 through 2007. The study examines the effects of the number and identity of co-managers on five components of flotation costs of SEOs. The results of empirical tests suggest that underwriting spreads are significantly lower when highly prestigious underwriters or commercial banks are included as co-managers in a syndicate. Moreover, although it found that the number of co-managers has no significant effect on the indirect components of flotation costs, the relationship between the number of co-managers and spreads is quadratic with spreads first increasing, but ultimately decreasing with the number of co-managers.

3.3. Studies on Indirect Flotation Costs

Except for those on SEO underpricing, studies on indirect flotation costs of SEOs include determinants of announcement effects, probability of issues being withdrawn and offer delays. Among those studies, those on announcement effects are in the majority. This is probably because only a small fraction of all issues experience issue withdrawal (failure) or delays¹⁸. Moreover, the announcement effects only exist in SEO studies. Since both underpricing and announcement effects are indirect flotation costs, underpricing is also used as a determinant to explain the announcement effects (e.g. Altinkilic and Hansen, 2003). Therefore, discussions on studies of indirect flotation costs (mainly announcement effects) have important implications for SEO underpricing.

3.3.1. Announcement Effects

Masulis and Korwar (1985) document on average a negative stock price change on the announcement of seasoned equity offerings. Their sample contained 972 primary stock offerings, 242 combination primary and secondary stock offerings and 182 dual debt and equity offerings from 1963 to 1980. The study found evidence that the information conveyed by the offerings was much greater for industrial firms than for public utilities, which can be partially explained by the high frequency of public utilities offerings.

¹⁸ For instance, the sample in Jeon and Ligon (2011) has 2071 completed SEOs but only 183 withdrawn SEOs during the sample period.

In the regression analysis of Masulis and Korwar (1985), the explanatory variables are percentage change in outstanding shares, changes in financial leverage, stock return volatility and a dummy variable indicating management share sales. The results support stock price changes proportional with the changes in management's fractional shareholdings in the firm. This finding is consistent with the agency model proposed by Jensen and Meckling (1976) and the signalling model proposed by Leland and Pyle (1977). They also found that the announcement period returns were positively related to leverage change, which is consistent with Masulis (1983).

Following Masulis and Korwar (1985), many empirical studies have documented the evidence of significantly negative reaction to seasoned equity offerings. For instance, Hansen and Crutchley (1990) document an announcement period abnormal return of -3.65% in their sample. The announcement period abnormal return is defined as an abnormal return in the period from 1 day prior to the announcement to the announcement date. Korajczyk et al. (1991) report significant negative average abnormal returns of -2.26% and -0.43% on the day preceding and the day of announcement, respectively. Denis (1991) found that the announcement period abnormal returns are -4.33% for non-shelf offerings and -3.62% for non-shelf offerings, and defines the announcement period abnormal return as the 2 day abnormal returns including the day and the day before the announcement of the seasoned equity offerings.

Using the same definition, Bayless and Chaplinsky (1996) recorded an average abnormal return of -2.5% over their sample period from 1974 to 1990. Chaplinsky and Ramchand (2000) compared the price reaction to the announcement of SEO for both

US issues and global issues. They define the price reaction of CAR (-1, 1) (the cumulative average abnormal return from day -1 and day +1), where day 0 represents the announcement or registration date of the offer. In the study, they reported CAR (-1, 1) of -2.4% for US offers and -2.2% for global offer.

Altinkilic and Hansen (2003) analysed the offer announcement price reaction. Their sample consisted of 1703 SEOs from 1990 to 1997. They report an announcement period abnormal return of -2.23%. The cross-section estimates of announcement period abnormal returns show that expected discounting has a statistically significant negative impact on the announcement reaction, indicating that investors account for expected discounting costs when they learn of the seasoned offer¹⁹.

3.3.2. Explanations for Announcement Effects

In this section, we first discuss three hypotheses summarised by Kalay and Shimrat (1987) namely the price-pressure hypothesis, the wealth redistribution hypothesis and the information release hypothesis. We then further discuss empirical models developed based on the information release hypothesis.

3.3.2.1. Three Hypotheses related to Announcement Effects

Kalay and Shimrat (1987) summarise three hypotheses related to announcement effects of seasoned equity offerings. The price-pressure hypothesis proposed by Scholes (1972) suggests that the demand curve for the shares offered is downward

¹⁹ In their regression, the announcement period abnormal return is the dependent variable while independent variables include firm size, relative amount, announcement period return on the CRSP index, expected discounting and the discrete measure of expected discounting.

sloping. Announcement of equity offerings means more shares will be poured into the market, thereby decreasing the price of the security. Mixed evidence is found in the literature for this hypothesis (e.g. Asquith and Mullins, 1986; Masulis and Korwar, 1985).

The wealth redistribution hypothesis argues that the decrease in the market value of the outstanding equity is accompanied by an increase in the market value of outstanding bonds. Due to the increase in the equity the leverage ratio of the firm decreases, making the debt less risky. As a result, the value lost by shareholders is granted to bondholders. Masulis and Korwar (1985) report a negative relation between the abnormal return on the announcement day and the leverage change caused by the issuance, but if the relative issue size is taken into consideration, the negative relationship no longer exists (Masulis and Korwar, 1985; Asquith and Mullins, 1986).

The third hypothesis is the information release hypothesis. Under that hypothesis, theoretical models (e.g. Leland and Pyle, 1977; Myers and Majluf, 1984; Miller and Rock, 1985) emphasise that the firm possesses superior information over outside investors. Therefore, the financing decision made by the firm can be seen as a signal of negative information.

Kalay and Shimrat (1987) tried to find out which of the three hypotheses is relatively the most important and used the effects on bond price made by the equity offerings to decide. The results of empirical tests suggest that bond prices are negatively related to the announcement of equity offerings. Therefore, Kalay and Shimrat (1987) conclude

that the information release hypothesis is the prevailing factor affecting the share prices, although, at the same time, the study does not rule out the other two hypotheses.

3.3.2.2. Adverse Selection, Agency Issues and Information Asymmetry

Models developed under the information release hypothesis are also called adverse selection models. Under the assumptions that managers are maximising the wealth of shareholders and capital markets are efficient, Myers and Majluf (1984) and Krasker (1986) predict that managers are more likely to issue equity when the current stock price rises relative to its intrinsic value. Rational investors then interpret the decision of equity offering as conveying management's opinion that the shares are not undervalued. This interpretation will truncate the right tail of the stock price probability distribution (stock undervaluation). As a result, the share price will decrease.

The alternative framework of adverse selection is agency issues. The agency models assume that managers often pursue their own private benefits. Therefore, firms are more likely to use the capital for agency spending, such as empire building. Jung et al. (1996) used book-market ratios as the proxy of investment opportunities and found that firms without valuable investment opportunities have more negative announcement returns than firms with better investment opportunities. They claim that their results strongly support the agency model.

Recently, Walker and Yost (2008) confirmed the negative announcement period abnormal return in their study. They define the abnormal return as a two day cumulative return CAR (0, +1), where day 0 is the announcement date. They found

that the average two-day abnormal announcement return is -2.76%. They collected the stated intentions for the proceeds received from SEO issues from firms' Securities and Exchange Commission equity registration filings, and the stated use of funds is primarily for investment (INVEST firms), debt reduction (DEBT firms) or for general corporate purposes (GENERAL firms). Walker and Yost (2008) found that regardless of what they say in the S-filing, firms increase investment at economically meaningful rates after SEO. However, the empirical results show a negative relationship between anticipated firm investment and abnormal returns for GENERAL firms, suggesting that the market reacts favourably to the anticipated seasoned equity offerings if the firm provides specific plans for the use of the soon-to-be-raised capital.

Based on both adverse selection and the alternative agency model framework, Lee and Masulis (2009) argue that poor accounting information prevents investors from evaluating the true financial status of the issuing firm and increases information asymmetry between issuers and investors. As a result, the increased asymmetric information leads to more adverse selections and moral hazards. Therefore, they propose a hypothesis that poor accounting information quality is associated with larger negative SEO announcement effects. The hypothesis is supported by the empirical results which show a significant negative coefficient of the accruals quality measures.

Another recent study also investigated the importance of information asymmetry on announcement effects. Jeon and Ligon (2011) examined the role of co-managers in reducing information asymmetries in SEO transactions and hypothesised that 1) the announcement return would increase the number of co-managers, if more co-managers can more accurately certify the value of the issuing firm; 2) announcement returns

would be positively associated with the inclusion of highly reputable co-managers and commercial banks co-managers, if they can reduce information asymmetries by credibly certifying the value of the securities. The results suggest that 1) the effect of the number of co-managers on increasing announcement returns is largely insignificant, and 2) co-managers with a high reputation serve a certification role, mitigating the information asymmetry in SEO, thus increasing the announcement return of SEOs.

Table 3-1 Summary of completed offers and withdrawals for IPO and SEO

Study	Time Period	No of Completed Offerings	No of Withdrawn Offerings	Sample Selection
Hao 2011	1996-2005	2284	594	US IPOs, excluding unit offers, ADRs, carve-out/spin-offs, reverse LBOs, partnerships and financial firms
Lee and Masulis 2009	1990-2002	963	89	US SEOs listed on NYSE, NASDAQ or Amex, excluding offers prices<\$5, spin-offs, reverse LBOs, closed-end fund, unit investment trusts, REITs, limited partnerships, rights and standby issues, unit offers and warrant, nondomestic and simultaneous domestic-international offers, offers with required financial data unavailable in Compustat
Jeon and Ligon 2011	1997-2007	2071	183	US SEOs listed on NYSE, NASDAQ or Amex, excluding offers prices<\$ 3 or price>\$400, financial and utility firms, Units, ADRs, REITs, limited partnerships, rights offerings, pure secondary offers, offers with required price and financial data unavailable in CRSP and Compustat

3.3.3. Issue Withdrawal and Offer Delays

Issue withdrawal occurs if an investment banking syndicate declines to underwrite an offering or an issuer chooses to cancel the equity offerings. Lee and Masulis (2009) summarise two parts of expected cost of issue withdrawal to an issuer: 1) the delay of valuable investment opportunities or turning to most costly sources of external capital;

2) registration fees, accounting expenses and management time devoted to the offering process.

Due to the high cost of issue withdrawal, it rarely occurs for both IPO and SEO transactions. Table 3-1 provides a summary of both completed offers and offer withdrawals for IPOs and SEOs. For IPOs, there is a higher ratio of withdrawals to completed offers. According to Hao (2011), there were 594 IPO withdrawals from 1996-2005, representing 26% of the total completed offers during the same time period. SEOs have a lower ratio of withdrawals to completed offers. Lee and Masulis (2009) report a ratio of 9.2% from 1990 to 2002, while Jeon and Ligon (2011) report 8.8% from 1997 to 2007.

Table 3-2 Factors affecting withdrawal probability

Study	Variables positively and significantly associated with the probability of offering withdrawal	Variables negatively and significantly associated with the probability of offering withdrawal	Regression Methods
Hao 2011	Ratio of withdrawn IPOs to completed IPOs and IPOs in active registration, industry daily return volatility, change in AAA-10 year treasury yield spread	Filing Amount, Technology dummy, utility dummy, Bank market share, number of IPO filings, average underpricing, industry return	Logit
Lee and Masulis 2009	Accruals quality, total assets, leverage, secondary shares, return volatility,	Net proceeds	Instrumental Variable Probit (IV-probit)
Jeon and Ligon 2011	Return volatility, leverage, Sarbanes-Oxely Act (SOX) dummy	Cumulative abnormal return (CAR), market-book ratio, market return, the inclusion of prestigious co-manager in the syndicate	Logit, Instrumental Variable Probit (IV-probit), Maximum-likelihood estimator (MLE), Instrumental variables model of average treatment effects (IV-ATE)

Variables affecting withdrawal probability are summarised in Table 3-2. Hao (2011) reports that for IPO withdrawals, issuer and issue characteristics (filing amount, technology dummy and utility dummy), investment bank characteristics (bank market share) and market conditions during registration period (number of IPO filings, ratio of withdrawn IPOs to completed IPOs and IPOs in active registration, average underpricing, industry return, industry daily return volatility and change in AAA-10 year Treasury yield spread) are associated with the withdrawal probability at a statistically significant level.

For SEOs, issuer and issue characteristics which have significant effects on the probability of offering withdrawal include accruals quality, total assets, leverage, net proceeds, market-book ratio, secondary shares, return volatility and cumulative abnormal return during the registration period (e.g. Lee and Masulis, 2009; Jeon and Ligon, 2011). Investment bank characteristics include the inclusion of a prestigious co-manager in the syndicate (Jeon and Ligon, 2011), while variables of market conditions include Sarbanes-Oxley Act dummy and market return.

Jeon and Ligon (2011) define the offer delay as the natural logarithm of the number of days during the registration period. They use the OLS regression as a base line model and 2SLS and treatment regressions to deal with the possible endogeneity. The empirical results suggest that offer delays are significantly and positively associated with asset, market-book ratio, pure primary dummy and market return and significantly and negatively associated with NASDAQ dummy, Sarbanes-Oxley Act dummy, active-market, underwriter rank, number of co-managers and the inclusion of a prestigious co-manager or commercial bank co-manager in the syndicate.

3.4. Reasons to Conduct Seasoned Equity Offerings (SEO)

In the literature, the reasons that explain why a firm conducts a seasoned equity offering (SEO) can be summarised in several categories, namely pecking-order theory, tax and leverage cost trade-off models, market timing, corporate lifecycle stage and near-term cash need. Table 3-3 summarises the reasons to issue a SEO under different theory frameworks.

Table 3-3 Reasons to conduct SEOs

Theory	Reason to Conduct SEOs	Studies
Pecking-order theory	The reason for a company to conduct an SEO is that all other measures cannot meet cash flows required by the investment opportunities.	Myers and Majluf (1984), Shyam-Sunder and Myers (1999), Leary and Roberts (2010)
Tax and leverage cost trade-off models	The reason for a company to issue equity offerings is the change in either equity or debt, or even the debt target ratio itself. In order to keep the target debt ratio, the company has to make equity offerings.	Modigliani and Merton (1958), Fama and French (2002), Flannery and Rangan (2006), Chang and Dasgupta (2009)
Market timing	Managers try to sell highly priced shares when stock market conditions permit.	Taggart (1977), Loughran and Ritter (1995), Loughran and Ritter (1997), Baker and Wurgler (2002), DeAngelo et al. (2010)
Corporate lifecycle stage	Young companies with high market-to-book ratios and low operating cash flows tend to sell equity to fund investment while mature companies prefer to fund investment internally.	Carlson et al. (2006), DeAngelo et al. (2010)
Near-term cash need	Issuers have to conduct SEOs in order to avoid running out of cash in the near term.	DeAngelo et al. (2010)

3.4.1. SEOs, Pecking Order Theory and Trade-off Models

Myers and Majluf's (1984) pecking order theory suggests that companies tend to rely on internal finance and prefer safe securities (e.g. debt) to risky ones (e.g. equity) if external finance is required. In short, when a company is facing investment opportunities, it tends to use retention first. If retention cannot meet the funding

requirement, the company will issue debt, then possibly hybrid securities such as convertible bonds and then equity as a last resort. Therefore, under the pecking order theory, the reason for a company to conduct an SEO is that all other measures cannot meet cash flows required by the investment opportunities.

The trade-off theory of capital structure proposed by Modigliani and Merton (1958) is described as a common practice adopted by companies in many finance textbooks (e.g. Brealey et al., 2006). Under this theory, the debt-equity decision can be viewed as a trade-off between interest tax shields and the costs of financial distress. Instead of suggesting that firms should take on as much debt as possible as the pecking order theory does, the trade-off theory argues that companies should take a target debt ratio which balances the benefits brought by interest tax shields and the costs of financial distress or bankruptcy. Therefore, according to the trade-off theory, the reason for a company to issue equity offerings is the change in either equity or debt, or even the debt target ratio itself. In order to keep the target debt ratio, the company has to make equity offerings.

3.4.2. Empirical Results of the Pecking Order and Trade-off Theory

Mixed evidence is found by a number of empirical studies related to the pecking order theory and trade-off theory. Table 3-4 summarises empirical studies related to the pecking-order and trade-off theories.

Table 3-4 Summary of empirical studies related to pecking-order and trade-off theory

Study	Sample	Methodologies	Conclusions
Shyam-Sunder and Myers (1999)	157 US firms from 1971-1989	OLS regression	The basic pecking order model is an excellent first-order descriptor of financing behaviour
Frank and Goyal (2003)	A sample of US publicly traded firms for 1971-1998. And the study does not require firms to survive during the sample period	OLS regression	Large firms exhibit some aspects of pecking order behavior but the evidence is not robust when conventional leverage factors are included nor when sample period is restricted to the 1990s.
Leary and Roberts (2010)	34470 firm-year observations over the period 1980-2005	Empirical model and simulation experiment	Even when controlling for the debt capacity, the pecking order is never able to accurately classify more than half of the observed financing decisions; The predictive accuracy of the model increases dramatically when factors typically attributed to alternative theories are incorporated; The both pecking order and trade-off models have elements of truth that help explain some aspects of financing decisions.
Fama and French (2002)	An average of about 1600 firms per regression over 35-year period (1965-1999)	Fama-MacBeth regressions	Two models share many predictions about dividends and leverage while the two models disagree on some issues. The trade-off model suffers a "scar" (it predicts negative relation between leverage and profitability while the relation is positive; and the rate of mean reversion predicted by the trade-off model is suspiciously slow
Flannery and Rangan (2006)	111,106 firm-year observations from 1965-2001	Fama-MacBeth regressions; Fixed-Effect Panel; IV Panel	The inconsistency of the adjustment speed between their study and other studies (e.g. Fama and French 2002) is attributed to the unwarranted, but testable, assumptions about the adjustment speed and/or the dynamic properties of target leverage.
Chang and Dasgupta (2009)	112035 firm-year observations from 1971-2004	Simulations	Existing tests of target behaviour based on leverage ratio changes might not be able to give conclusive results; in order to find out which tests are useful in identifying target behaviour, we need to look at financing behaviour (debt versus equity choices).
de Jong et al. (2010)	2259 US firms and 13338 firm-year observations from the Compustat and CRSP databases for the period of 1985-2005	Two-step GMM estimator; a fixed effects approach	The pecking order theory is a better descriptor of firms' issue decisions than the static trade-off theory while the static trade-off theory is a better descriptor for firms' purchase decisions

3.4.2.1. Empirical Results of the Pecking Order Theory

Shyam-Sunder and Myers (1999) tested the basic pecking order model, which predicts external debt financing driven by the internal financial deficit. They estimated an OLS regression of a firm's net/gross debt issued (scaled by the book value of assets) on its financing deficit for a small sample of 157 firms that survived from 1971 to 1989. They found that the basic pecking order model has much greater time-series explanatory power than a static trade-off model, and conclude that the basic pecking order model is an excellent first order descriptor of financing behaviour.

Frank and Goyal (2003) selected a sample of US publicly traded firms in Compustat from the period 1971-1998. The study did not require firms to survive during the sample period. They estimate the same regression as that in Shyam-Sunder and Myers (1999) and found that the pecking order theory is a poor descriptor of firms' financing behaviour for the whole sample. Specifically, they found that large firms exhibit some aspects of pecking order behaviour, but the evidence is not robust when conventional leverage factors are included into the analysis, nor when the sample period is restricted to the 1990s.

Furthermore, Frank and Goyal (2003) argue that over time support for the pecking order theory declines and they attribute two reasons to the decline. One is that more small firms are listed publicly over time and small firms often do not follow the pecking order. The other is that for the quartile of largest firms, support for the pecking order theory declines over time, suggesting that equity becomes more important.

Fama and French (2005) also found evidence that is contrary to Shyam-Sunder and Myers (1999). In their sample, equity issues are both commonplace and on average large. Thus their results reject the central predictions of pecking order theory about how often and under what circumstances firms issue and repurchase equity. Given the contradictions of the trade-off model's central predictions documented in much previous work (e.g. Fama and French, 2002), they argue that both the pecking order model and the trade-off model have serious problems and suggest that a combination of the two models can better explain the financing decisions.

Leary and Roberts (2010) conducted an empirical test with a sample of 34470 firm-year observations over the period 1980-2005 drawn from Compustat. They developed an empirical model and a simulation experiment to test the prediction accuracy of the pecking-order theory. They found that fewer than 20% of firms followed the pecking order predictions concerning debt and equity issuance decisions under the strict interpretation of pecking order that limits the variation in firms' saving and debt policies. This result remains the same even after relaxing the strict interpretation and allowing firms' debt capacity to vary in a manner consistent with that of investment-grade rated firms in the same industry.

However, when the debt capacities of the firms are allowed to vary with variables often attributed to alternative theories (e.g. trade-off theory), the predictive capacity of pecking order theory improves significantly: over 80% of the observed debt and equity issuance decisions can be accurately classified. Leary and Roberts (2010) argue that their findings are consistent with Fama and French (2005), who suggested that

both pecking order and trade-off models have elements of truth that help explain some aspects of financing decisions.

3.4.2.2. Empirical Results of the Trade-off Theory

Fama and French (2002) tested both the pecking order model and trade-off model. They summarise that the two models share many predictions about dividends and leverage while the two models disagree on some issues. Figure 3-1 shows the shared predictions and disagreements between two models. Both models predict 1) negative relationship between investment and book leverage; 2) positive relationship between firm size and leverage dividend payout; 3) negative marginal relationship between leverage and the target dividend payout ratio. All of the above predictions are supported by empirical results.

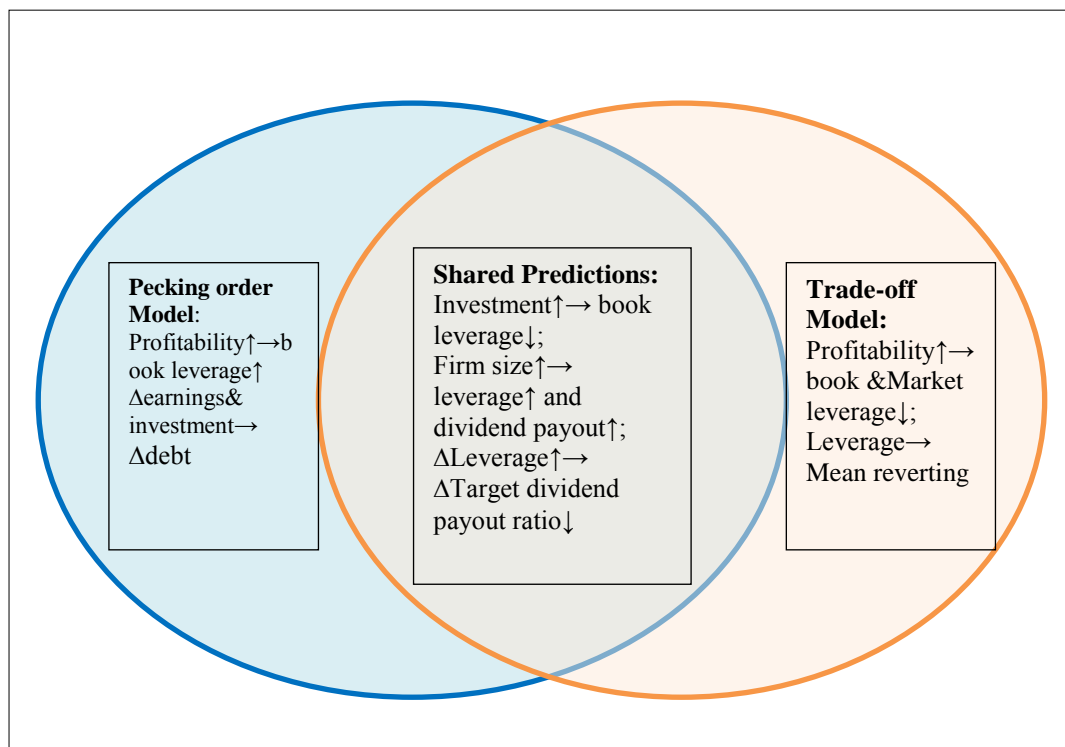


Figure 3-1 Shared predictions and disagreements between trade-off model and pecking order model

Although the trade-off model predicts a negative relationship between leverage and profitability, empirical results in Fama and French (2002) show a positive relationship. This failure is called a “scar” by Fama and French (2002). Moreover, despite there being evidence for the mean reverting of leverage target, they found that the rate of mean reversion (7-17% per year) was suspiciously slow.

Table 3-5 Effects of exclusion of partial adjustment and firm fixed effects on the adjustment Speed

Assumptions	Examples of Studies	Effect	Conclusions from Flannery and Rangan 2006
A firm's observed capital ratio is also its desired (target) ratio; when the market debt ratio (MDR) is the dependent variable, the coefficient on lagged MDR is zero	Fama and French 2002	When the lagged MDR is added, it has a very highly significant coefficient, thus ignoring lagged MDR would lead to an incorrect model specification	Partial adjustment toward a target capital ratio exists
Firm fixed effect could be excluded	Fama and French 2002, Baker and Wurgler 2002, Huang and Ritter 2009	Firm-specific unobserved effects substantially influence estimated adjustment speeds, apparently because they substantially sharpen estimates of the target debt ratio	Exclusion of firm fixed effects is unwarranted
Target measurement noise could be included	Flannery and Rangan 2006	Adding target measurement noise would biases the estimated coefficient on MDR toward unity. A noise volatility of 20% to 25% roughly halves the estimated adjustment speed from 34.5% to about 17%	The effect of noisy targets on the estimated adjustment speed is substantial

Contrary to the slow rate of mean reversion found by Fama and French (2002), Flannery and Rangan (2006) found that firms move relatively quickly towards their target debt ratio. In their study, the typical firm has a rate of mean reversion of more than 30% per year. Flannery and Rangan (2006) attribute the inconsistency of the adjustment speed between their study and other studies (e.g. Fama and French, 2002)

to the unwarranted, but testable, assumptions about the adjustment speed and/or the dynamic properties of target leverage. Table 3-5 shows the effects of exclusion of partial adjustment and firm fixed effects on the adjustment speed summarised by Flannery and Rangan (2006).

Chang and Dasgupta (2009) demonstrated that it is possible to observe target adjustment behaviour, direct rebalancing behaviour and significant firm-specific variables in leverage regressions even in samples through simulations in which no target behaviour is assumed. Therefore, they argue that existing tests of target behaviour based on leverage ratio changes might not be able to give conclusive results. Moreover, they suggest that in order to find out which tests are useful in identifying target behaviour, we need to look at financing behaviour (debt versus equity choices). Table 3-6 illustrates conclusions drawn from test results on simulation samples under three types of tests.

Table 3-6 Conclusions based on simulation samples

Tests	Representative studies	Results on simulation samples	Conclusions
Adjustment speeds	Fama and French 2002, Flannery and Rangan 2006	A move from random financing to vigorous target behaviour generates only a 10% change in the estimated speed of adjustment	The estimated speeds of adjustment are likely to provide a very imprecise picture of the extent of rebalancing going on in the data
Direct evidence of rebalancing behaviour	Leary and Roberts 2005, Altı 2006, Kayhan and Titman 2006	Mechanical effects could arise when firms do not follow target behaviour.	Tests of rebalancing behaviour do not have the power to reject mechanical effects associated with non-target behaviour
Significant effects of firm-specific variables in leverage regressions	Frank and Goyal 2007	Even for simulation samples, several firm-specific variables are statistically significant in leverage regressions	It is difficult to conclude the observed relationship between a particular firm-specific variable and the leverage ratio in the actual sample

de Jong et al. (2011) focus on financing decisions for which the trade-off theory and the pecking order theory have different predictions. Their sample includes a broad cross-section of US firms from the Compustat and CRSP databases for the period 1985-2005. They found that for issuing decisions, in more than three-quarters of the observations, over-leveraged firms still increased their leverage by issuing debt. This evidence suggests that the pecking order theory is a better descriptor of firms' issue decisions than the static trade-off theory. For under-leveraged firms that do have sufficient debt outstanding to be repurchased, they found that the majority of observations repurchase equity, which is evidence for the static trade-off theory for repurchase decisions.

3.4.3. Equity Market Timing

Because both the pecking order theory and the trade-off model are problematic (e.g. Fama and French, 2002; Leary and Roberts, 2010), studies on SEO have developed other explanations for the reason(s) of conducting SEOs specifically. Among them, one popular explanation is the market timing hypothesis, which suggests that managers try to sell highly priced shares when stock market conditions permit.

Baker and Wurgler (2002) summarise the evidence for market timing in four different kinds of study. The first kind of study shows that firms tend to issue equity rather than debt when market value is high²⁰, and tend to repurchase equity when market value is low. In the second kind, analyses of long-run post issue stock returns suggest that

²⁰ The high (low) valuation can be indicated by both high (low) market-to-book ratio and high (low) pre-issue return.

issuers are, on average, successful at equity marketing timing. In the third kind, analyses of profitability forecasts and realisations around equity issues suggest that firms tend to issue equity at times when investors are over-optimistic about earnings prospects. In the fourth kind, anonymous surveys show that managers admit to market timing (see Graham and Harvey, 2001).

3.4.3.1. Market-to-book Ratio and Stock Return

Market-to-book ratio as well as its various transformations is employed in equity market timing studies to identify mispricing. For instance, Baker and Wurgler (2002) employed a historical market-to-book ratio to capture firms' past equity market timing attempts²¹. After controlling for current investment opportunities in the form of current market-to-book ratio, the historical market-to-book ratio could be interpreted as a proxy of mispricing. They found an inverse relationship between leverage and the historical market-to-book ratio, which is interpreted as providing evidence to support the market timing hypothesis.

As discussed in the previous section, in the trade-off framework, market-to-book ratio is often used as a measure of growth options (e.g. Fama and French, 2002). High market-to-book ratios can be viewed as a sign of high growth options. Therefore, it is important to control for firms' growth opportunities when interpreting market-to-book ratio as an indicator of mispricing.

²¹ The ratio is called external finance weighted average market-to-book ratio in Baker and Wurgler (2002).

Hertzel and Li (2010) employed a methodology proposed by Rhodes–Kropf et al. (2005) (RKRK) that decomposes pre-issue market-to-book (MTB) ratios into misevaluation and growth option components²². They found that compared with the overall market, issuing firms have greater mispricing and greater growth options. They interpret this finding as evidence supporting the fact that both firm-level overvaluation and financing needs affect managerial decisions to issue equity.

Besides market-to-book ratio, studies have also tried to use pre-issue return to capture the marketing timing attempts. For instance, Hovakimian et al. (2001) found that firms with large stock price increases are more likely to issue equity and retire debt than firms with stock price declines. Graham and Harvey (2001) conducted a survey study and found that recent stock price performance is considered by managers as one of the most important factors affecting the equity issuance decision.

Moreover, Alti and Sulaeman (2012) looked at the timing behaviour and document that equity issues tend to follow periods of high stock returns. They found that stock price increases have a significant impact on the likelihood of equity issuance only when accompanied by institutional purchases. When institutional investor demand is weak, there is little evidence supporting such timing behaviour. The study provides evidence for an important certification role played by institutional investors in equity issues.

²² The methodology is developed to identify misevaluation in merger and acquisition activities by Rhodes–Kropf et al. (2005). The RKRK (2005) breaks MTB ratios into three components: firm-specific error (FSE), time-series sector error (TSSE) and long-run value-to-book (LRVTB).

3.4.3.2. Long-run Post-issue Underperformance

Market timing can be detected ex post by examining long-run stock returns of issuers. Loughran and Ritter (1995) document that firms issuing either IPOs or SEOs during 1970 to 1990 had low long-run return over the five years after the issue. After considering a number of possible explanations²³, the low long-run return still cannot be fully explained. Therefore, they suggest that another possible explanation is that firms tend to take advantage of transitory windows of opportunity by issuing equity when, on average, they are overvalued. Following Loughran and Ritter (1995), Loughran and Ritter (1997) document the larger declines of profit margin and return for issuers than nonissuers within four years of the offering in their sample of SEOs from 1979-1989.

However, some studies propose alternative explanations to the long-run underperformance based on return benchmark misspecification. Brav et al. (2000) found that in event time performance tests IPO returns are similar to nonissuing firm returns matched on firm size and book-to-market ratios. While SEO returns show some underperformance relative to various characteristic-based benchmarks, time series factor models show that SEO returns covary with nonissuing firm returns. Moreover, Brav et al. (2000) show that model misspecification could be an important consideration in long run performance tests²⁴.

²³ Loughran and Ritter (1995) found the low returns of issuers cannot be explained by the three-factor model proposed by Fama and French (1993).

²⁴ Brav et al. (2000) make small changes to the factor specification in Fama and French's model and improve its ability to price equity issuer returns as well as commonly used test portfolios.

Eckbo et al. (2000) note the fact that issuer stocks are on average less risky than stocks of matched firms due to changes in unexpected inflation and default risk and stock liquidity caused by equity issues. Thus, issuer stocks require lower expected returns than those of firms matched on size and book-to-market ratios. They argue that the abnormal performance is explained by a failure of the matched firm technique of Loughran and Ritter (1995). Carlson et al. (2006) also demonstrate that standard matching procedures fail to fully capture the dynamics of risk and expected return by developing a real options theory of observed returns throughout the SEO episode. They argue that expected returns of issuer stocks decrease because growth options are converted into assets with less risk in place.

As discussed in the previous section, Hertznel and Li (2010) break book-to-market ratios into three components. They found that in calendar-time factor regressions, SEO firms with high misvaluation have significant negative abnormal returns²⁵. Even after including an investment factor proposed by Lyandres et al. (2008), firm-level misvaluation still plays a statistically significant and economically important role in explaining the underperformance. Moreover, they found no relationship between post-issue abnormal returns and the pre-issue growth option component of MTB. The evidence, together with their finding that issuing firms with more growth options have higher levels of post-issue investment, is inconsistent with the real investment explanations of low post-issue stock returns.

²⁵ Misvaluation is measured by firm-specific error (FSE) in Hertznel and Li (2010).

Alti and Sulaeman (2012) used two approaches to detect SEO long-run return performance, namely event-time and calendar-time. The event-time approach is mainly used in a descriptive analysis because statistical inference based on event-time long-run returns is problematic (see, e.g. Brav, 2000). In the calendar-time approach, long-run returns exhibit significantly negative alphas in the five years following the offer. Moreover, Alti and Sulaeman (2012) found that insitutional demand for issuers' stocks has insignificant effects on the underperformance. Thus they conclude that the institutional demand effects are unrelated to the long-run underperformance phenomenon.

3.4.3.3. Other Empirical Studies related to Market Timing

Mahajan and Tartaroglu (2008) conducted empirical research to test the equity market timing hypothesis in major industrialised G-7 countries²⁶. Although they found that historical market-to-book ratio is inversely related to leverage in most industrialised countries, they also show that firms in G-7 countries, except Japan, fully rebalance their capital structure after equity issuance. Furthermore, they document a negative relationship between current market-to-book ratio with book leverage for US and Canadian firms when historical market-to-book ratio is included in the regressions. This result is consistent with the trade-off framework.

Hovakimian and Hutton (2010) found evidence inconsistent with the market timing hypothesis. In their research, they tested and found support for the market feedback hypothesis for a sample of firms that issue seasoned equity repeatedly. The hypothesis

²⁶ G-7 countries include the seven most industrialised countries: Canada, France, Germany, Italy, Japan, UK and US.

first proposed by Jegadeesh et al. (1993) suggests that high post-issue performance conveys the market's belief that the marginal return to the firm's projects is high, encouraging managers to raise additional capital to increase the firm's investment. Additionally, they also found some support for the role of institutional investors in the market feedback mechanism.

Jenter et al. (2011) examined the market timing hypothesis in a sample of put option sales on company stocks by large US firms. Previous studies examining equity issues have often suffered from 1) difficulty in interpreting equity issues and repurchases and 2) the problems associated with measuring abnormal returns over long periods of time. However, the put option sale setting provides a cleaner test by helping address the issues of both motivation and measurement. When the stocks are undervalued, managers tend to issue puts. They document a 5% abnormal stock return in the 100 days following put option issues, with much of the abnormal return following the first earnings release date after the sale. This result suggests that managers can identify mispricing equity and use securities issues to time the market.

3.4.4. Other Explanations for Conducting SEO

Besides the above explanations, DeAngelo et al. (2010) also try to give their opinions about the reasons to conduct SEOs. They propose two explanations for conducting SEOs, namely corporate lifecycle and near-term cash need. Under the theory of lifecycle, young companies with high market-to-book ratios and low operating cash flows tend to sell equity to fund investment while mature companies prefer to fund investment internally. Because these growth-stage issuers take a large portion of

issuers, the pre-SEO share price increases reflect an increase in the value of growth options. When the growth options are converted into assets in place, expected return declines endogenously (Carlson et al., 2006).

DeAngelo et al. (2010) found that both the market-timing and corporate lifecycle theory have a statistically significant influence on the decision to conduct an SEO, with the lifecycle effect being empirically stronger. They argue that neither theory adequately explains SEO decisions because the majority of issuers are not growth firms and the vast majority of firms with good market-timing opportunities fail to issue stock. Therefore, DeAngelo et al. (2010) conclude that a near-term cash need is the primary SEO motive by citing that 62.6% of issuers would run out of cash (81.1% would have subnormal cash balances) the year after the SEO without the offer proceeds.

Table 3-7 Magnitudes of IPO underpricing

Studies	Sample Period	Sample Size	Average IPO Underpricing
Liu and Ritter 2011	1980-2008	7319 IPOs	18.20%
Lowry et al 2010	1965-2005	8759 IPOs	22%
Loughran and Ritter 2004	1980-2003	6391 IPOs	18.70%

3.5. Introduction of SEO Underpricing

IPO underpricing has been confirmed as a consistent feature in the literature. For instance, Lowry et al. (2010) found that IPO underpricing averaged 22% between 1965 and 2005 in the US market, and the means of initial returns for 1965-1980, 1981-1990, and 1991-2005 were 12.1%, 9.2% and 25.8% respectively. A number of studies

also document considerable IPO underpricing in the US market. Table 3-7 summarises IPO underpricing reported by previous studies.

Table 3-8 Magnitudes of SEO underpricing and discount

Studies	Sample Period	Sample Size	Average SEO Underpricing/discount
Altinkilic and Hansen 2003	1990-1997	1703 SEOs	Average SEO Discount: 2.47%; Average SEO Underpricing: 2.58%
Corwin 2003	1980-1998	4454 SEOs	Average SEO Discount: 2.21%
Mola and Loughran 2004	1986-1999	4814 SEOs	Average SEO Discount: 3.0%
Kim and Shin 2004	1983-1998	3034 SEOs	Average SEO Discount: 2.02%
Kim and Park 2005	1989-2000	1040 SEOs	Average SEO Underpricing: 3.45%
Chammanur et al 2009	1999-2004	1108 SEOs	Average SEO Discount: 2.97%; Average SEO Underpricing: 3.50%
Autore 2011	1982-2006	4661 SEOs	Average SEO Discount: 2.30%
Jeon and Ligon 2011	1997-2007	2071 SEOs	Average SEO Underpricing: 3.04%
Huang and Zhang 2011	1995 -2004	2281 SEOs	Average SEO Discount: 3.16%

While IPO underpricing in the US market was significant as early as the 1960s, SEO underpricing was relatively stable until the 1990s. Table 3-8 shows average SEO underpricing/discount reported by previous studies²⁷. The average SEO underpricing was around 2-3% in the period 1980-2000. Compared with IPO underpricing, SEO underpricing has a relatively smaller magnitude. Moreover, a number of studies document relatively low SEO underpricing during the 1980s. For instance, Corwin (2003) reports that average SEO discount in the 1980s in his sample was 1.15% while the mean discount from 1990 to 1998 was 2.92%. Mola and Loughran (2004) found that average SEO discount from 1986 to 1989 was 1.1%. According to the results

²⁷ The definitions of SEO underpricing and discount vary among studies. Since SEO underpricing and discount are analogous, we include studies of both SEO underpricing and discount in this section. In this chapter, SEO underpricing and discount refer to terms defined by the cited studies. In Chapter Four, differences between these terms are discussed.

from previous studies, we can conclude that SEO underpricing has increased substantially from the 1980s to the 1990s.

3.6. Determinants of SEO Underpricing

In this section we discuss several important theoretical models about IPO and SEO underpricing. Through these discussions, we can identify which factors affect SEO underpricing. We discuss the empirical studies on SEO underpricing and identify which proxies are employed in the literature to represent those factors identified by theoretical models.

3.6.1. Theoretical Models of Equity Offering Underpricing

We summarise a number of IPO underpricing models and three SEO underpricing models in this section. Some conclusions drawn from IPO underpricing models, such as oligopoly market proposed by Liu and Ritter (2011), might be possibly applied in SEO underpricing.

3.6.1.1. IPO Underpricing Models

A number of studies on equity offerings provide theoretical models of underpricing. Some factors identified by theoretical models in IPO underpricing can also be applied in SEO underpricing²⁸. Thus, the following discussions also include some important models in IPO underpricing. A number of studies propose their own theoretical explanations about IPO underpricing. These explanations are mainly information

²⁸ This practice is applied by a number of empirical studies in SEO underpricing (e.g. Altinkilic and Hansen, 2003).

asymmetry oriented. There are two main dimensions, namely interaction between the underwriter and investors and interaction between the underwriter and the issuers.

Interaction between the underwriter and investors

Rock (1986) proposed a theoretical model explaining why unseasoned issues may be sold at a price below market value. Rock's model is based on the information asymmetry among investors. The fundamental assumption of his model is that there is a group of investors with information superior to that in the firm as well as that of all other investors. The rationale for the model is that uninformed investors expect the offer to be oversubscribed if the offer price is too high and undersubscribed if the offer price is too low. Informed investors crowd the uninformed out of some offerings and they withdraw from others; uninformed investors give up good shares and buy bad shares. In order to induce a sufficient number of uninformed investors, issuers have to price the shares at a discount to overcome the bias.

Rock (1986) argued that investors should receive higher compensation in the form of underpricing when it is more difficult to value the firm in IPO transactions. Benveniste and Spindt (1989) proposed a dynamic information acquisition model for IPOs and argue that, in order to obtain truthful demand information in the book-building phase, underwriters should reward regular investors with more underpricing in the deals for which there is a strong demand. Thus, deals in which the offer price is revised upwards pay more through underpricing for information provided by the better-informed investors. The model provides important theoretical support for the argument that new issues will be underpriced and that the distributional priority will be given to an underwriter's regular investors.

Welch (1992) proposed a “cascade” model to explain the pricing decisions of IPOs. The model assumes that when IPO shares are sold sequentially, later investors can learn from the purchasing decisions of earlier investors and then rely completely on those purchasing decisions and ignore their own private information about the offering. The model predicts that demand of the offerings can be so elastic that even risk-neutral issuers have to underprice their offerings in order to completely avoid failure.

Interaction between the underwriter and the issuers

Regarding the interaction between the underwriter and the issuers, Baron (1982) provides a theoretical model to deal with the asymmetric information between the issuer and the banker. He assumes that the banker is better informed than the issuer about the capital market. If both the issuer and the banker are equally informed about the capital market, a firm commitment contract can be viewed as optimal and the banker would provide the distribution service at the first-best level²⁹. When the banker has superior information, the issuer is unable to observe the distribution efforts made by the bank, causing the banker to spend efforts less than the first-best effort level under a pure distribution contract.

As a result there is therefore room for the bank to add advertising services to a pure distribution service. Under this contract, the offer price is delegated to the banker who has the superior information about the capital market. Because the banker uses superior information, the issuer has to compensate for this additional service.

²⁹ First-best level means that the banker endeavours to provide the best distribution service it can. It does not mean the contract is a best-effort one (indeed the contract is a firm-commitment one).

Therefore, the optimal offer price is set below the first-best offer price, causing the offer to be underpriced when the bank is better informed than the issuer.

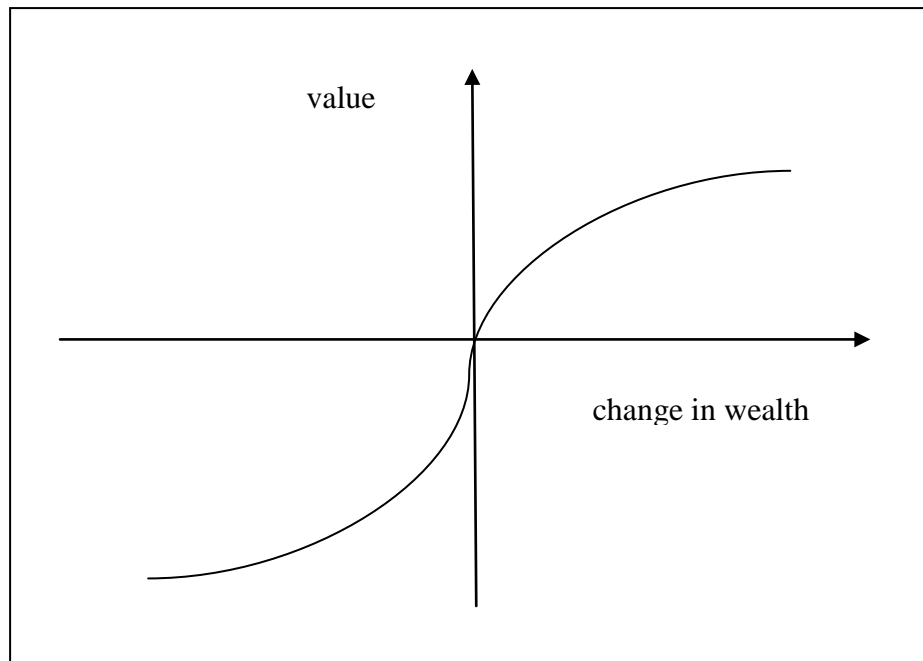


Figure 3-2 Prospect theory's value function (Loughran and Ritter, 2002, p422)

Loughran and Ritter (2002) present a prospect theory model that focuses on the covariance of the money left on the table and the issuer's wealth changes. The theory argues that 1) each individual has a value function; 2) the value function is concave in gains and convex in losses; 3) the value function is steeper for small losses than for small gains; 4) when an individual faces a gain and a loss, whether the individual feels better by integrating or segregating the events depends upon their magnitudes. Figure 3-2 illustrates the value function.

A shareholder i will have greater wealth gain than his or her share of the money left on the table when the following condition is met:

$$\begin{aligned}
& [shares\ retained_i + secondary\ shares\ sold_i][OP - midpoint] + \\
& shares\ retained_i[P - OP] > \\
& [P - OP][secondary\ shares\ sold_i + primary\ shares\ sold\left(\frac{shares\ retained_i}{shares\ retained}\right)]
\end{aligned}$$

where P is the market price, OP is the offer price, *primary shares sold* are shares being sold by the firm, *secondary shares sold_i* are existing shares being sold by shareholder i , and the *shares retained* are for all shareholders combined. When the above condition is met, a preissue shareholder will integrate the loss and the gain and accept high IPO underpricing.

Liu and Ritter (2011) developed a model based on differentiated underwriting services to explain IPO underpricing. Following previous studies (e.g. Hoberg, 2007), the model assumes an imperfect underwriting market where underwriters collude and charge the same level of underpricing. The underlining rationale for the imperfect underwriting market is that issuers care about non-price dimensions of underwriting such as analyst coverage. Thus a limited number of underwriters that have the capacity to provide these non-price dimensions will acquire some market power and earn rents on the IPOs. In this case, the underwriting market can be characterised as a series of local oligopolies.

In the model, the collusion underpricing is deduced as follows. $\dot{U} = \bar{U} + \frac{\gamma A + C}{2\gamma}$, where \dot{U} is the collusion value of underpricing, \bar{U} is the dollar amount of underpricing needed to compensate investors for the ex-ante uncertainties of issue valuation, C is the cost

of providing all-star analyst coverage and γ is the fraction of the money left on the table that is received by the underwriters.

Under a trigger strategy proposed by Green and Porter (1984), these underwriters can maintain the collusive underpricing level given a sufficiently low discount rate i^{30} , and underwriters with all-star analysts in an industry can form a local oligopoly and earn oligopoly profits. For an underwriter with an all-star analyst, the level of underpricing is $\dot{U} = \bar{U} + \frac{\gamma A + C}{2\gamma}$, and the underwriter without an all-star analyst charges $U = \bar{U}$.

3.6.1.2. SEO Underpricing Models

Compared with IPO theoretical models, theoretical models of SEO underpricing are fewer. Three important theoretical models are discussed in this section. Parsons and Raviv (1985) provided the first framework for information asymmetry in SEO underpricing. Their model assumes that a firm raises funds for a future investment with uncertain revenue. The formulation is based on two market stages, namely the competitive market in the old shares after the announcement and before the issue and the market with new issues sold on the part of the underwriter. The investors are divided into two types with different expectations of the revenue of the firm's investment. Based on these settings, the equilibrium price is calculated under different propositions.

The insight gained from the model is that the market prices and the offer price are jointly determined in the equilibrium. As a result, the banker cannot simply set the

³⁰ Liu and Ritter assume there are three underwriters in the oligopoly.

offer price to correspond to the current market price. More importantly, the study points out that restriction against short selling is a critical assumption, showing that short-sale restrictions make existing share prices less informative and cause the underwriters to give larger discounts to counteract the uncertainty. As we will discuss in the following section, this important finding related to short-sale/price manipulation is cited frequently by many empirical studies (e.g. Corwin, 2003; Altinkilic and Hansen, 2003; Kim and Shin, 2004).

Gerard and Nanda (1993) developed a model of manipulative informed trading around SEOs to explain SEO underpricing. The model follows the microstructure in Kyle (1985) and predicts that increases in selling prior to an SEO leads to increases in the market maker's inventory and temporary price decreases. Specifically, informed traders attempt to manipulate offering prices by selling shares prior to the SEO, then they bid shares in the offerings at lower prices and profit subsequently.

The equilibrium concept used in Gerard and Nanda (1993) is Sequential Nash. The underlining rationale is summarised as follows. Under risk neutrality, market makers will set the secondary market clearing price at:

$$P_Q = E[\tilde{V}|Q] \tag{3.1}$$

where $E[\tilde{V}|Q]$ represents the expectation of the asset value given the net order flow observed by market participants and cleared by the market maker Q .

The issuer will set the offering price P_Q^* such that, given the observed net order flow in the secondary market, uninformed bidders' expected payoffs from bidding are zero.

$$P_Q^* = E[\tilde{V}|Q] + \frac{Cov[\tilde{\alpha}_U, \tilde{V}|Q]}{E[\tilde{\alpha}_U|Q]} \quad (3.2)$$

where $\tilde{\alpha}_U$ represents the number of new shares allocated to uninformed bidders. According to equation (3.2), the offering price P_Q^* is always lower or equal to the expected terminal value of the security conditional on all public information.

$$P_Q^* \leq E[\tilde{V}|Q] \quad (3.3)$$

The informed investor may have negative or positive information about the offering. For the former case, the informed investor will always submit an order $Q_1^{-*} = -1$.³¹ For the latter case there are three possible orders $Q_1^{+*} = -1$, $Q_1^{+*} = 0$, and $Q_1^{+*} = +1$. Thus Gerard and Nanda (1993) summarise three pure strategy equilibria which are referred as equilibria M, PM and NM. Under each equilibrium, the net order flow can be ranged and then the market clearing price and offer price can be computed using equation (1) and (2) respectively. These results are listed in Table 3-9.

The M equilibrium is the pure manipulation equilibrium. Under this equilibrium, $Q_1^{-*} = -1$ and $Q_1^{+*} = -1$, which means the informed trader always sells in the

³¹ Gerard and Nanda (1993) set five time points in the model. The subscript 1 for Q_1^{-*} means time point 1, which represents the time of trading in a secondary market. The superscript $-/+$ represents the negative/positive information, and there is an assumption that the informed trader secondary market sales are restricted to -1 prior to the SEO.

secondary market regardless of whether the information is positive or negative. This strategy is still profitable for the informed trader as long as the loss from the secondary market trading is smaller than the additional gain from a lower issue price. The net order flow is $Q \in \{-2, -1, 0\}$. Under the M equilibrium, the net order flow is independent of the information and therefore is uninformative. The equilibrium market clearing price and offer price are denoted as P_0 and P_0^* .

Table 3-9 SEO price and market clear price under three equilibria

	Q	P_Q	P_Q^*	Conditions
The M Equilibrium	0, -1, -2	\bar{V}	$V^- + \frac{\Delta V}{1 + \beta}$	$\alpha_1 \geq \frac{1}{2\gamma} \times \frac{1+\beta}{\beta}$ (Ia) $\alpha_{l\geq} \geq \frac{1+\gamma}{2(1-\gamma)} \times \frac{1+\beta}{\beta}$ (Ib)
The PM Equilibrium	+1	V^+	V^+	$\alpha_l \leq \left[1 - \frac{2\gamma(1-2\gamma)}{1-\gamma}\right] / \left[\gamma + (1 - 3\gamma) \left[\frac{(1-2\gamma)}{(1-2\gamma)+\beta\gamma} - \frac{\gamma}{\gamma+\beta(1-2\gamma)}\right]\right]$ (Ila) $\alpha_l \geq \frac{\gamma^2}{1-\gamma} / \left[(1-2\gamma) - \frac{(1-3\gamma)(1-2\gamma)}{(1-2\gamma)+\beta\gamma} - \frac{\gamma^2}{\gamma+\beta(1-2\gamma)}\right]$ (IIb)
	0	$V^- + \Delta V \frac{1-2\gamma}{1-\gamma}$	$V^- + \Delta V \frac{(1-2\gamma)}{(1-\gamma) + \beta\gamma}$	
	-1	$V^- + \Delta V \frac{\gamma}{1-\gamma}$	$V^- + \Delta V \frac{\gamma}{(1-2\gamma)\beta + \gamma}$	
	-2	V^-	V^-	
The NM Equilibrium	+2, +1	V^+	V^+	$\alpha_l \leq \frac{\gamma(1+\beta)}{2[\beta(1-2\gamma)+\gamma]}$, (IIIa) $\alpha_l \leq \frac{1}{(1-\gamma)}$, (IIIb)
	0	V^-	$V^- + \Delta V \frac{1}{1+\beta}$	
	-2, -1	V^-	V^-	

Furthermore, the PM equilibrium is the partial manipulation equilibrium. The optimal strategy for the informed trader is to not trade in the secondary market ($Q_1^{+*} = 0$) if the information is positive (V^+) and to submit an order $Q_1^{-*} = -1$ if the information is

negative (V^-). The net order flow is $Q \in \{-2, -1, 0, +1\}$. Last but not least, the NM equilibrium means non-manipulation equilibrium. Under this equilibrium, the informed trader will not conceal the information and profit from the secondary market trading directly. $Q_1^{+*} = +1$ if the information is V^+ and $Q_1^{-*} = -1$ if the information is V^- . The net order flow is then $Q \in \{-2, -1, 0, +1, +2\}$.

Besides pure strategy equilibria, Gerard and Nanda (1993) also considered two types of mixed equilibrium, namely MX1 and MX2. The informed trader with positive information mixes between trading $Q_1^{+*} = -1$ and $Q_1^{+*} = 0$ in the equilibrium MX1 while the informed trader mixes between trading $Q_1^{+*} = 0$ and $Q_1^{+*} = +1$ in the equilibrium MX2. For both equilibria, the secondary market clearing prices and the offer prices are presented in Gerard and Nanda (1993).

Recently, Chemmanur and Jiao (2011) developed a model of the SEO process. Similar to Gerard and Nanda (1993), the model starts from the SEO announcement, through pre-offer trading, and ends in the offering itself. But the model emphasises the role of institutional investors in the SEO process, especially their information production role. Chemmanur and Jiao (2011) propose a series of propositions based on the model, and among them, several propositions are directly related to SEO discount and underpricing. Specifically, the model predicts that 1) the issuer always offers an SEO discount to investors in the SEO equilibrium; 2) there is a positive link between the SEO discount and the extent of information asymmetry; 3) SEOs with greater pre-offer net buying by institutional investors have higher institutional allocations, greater oversubscription and lower SEO discounts.

In the model, firm insiders hold all m shares of the all equity firm. The firm can be type H (the "high" type with cash flow of h at time 3) or type L (the "low" type with cash flow of l at time 3)³². Outsider investors believe that the firm is of type H with probability θ and of type L with probability $1 - \theta$. For the type H and type L firms, with a probability α_H and α_L respectively, a fraction λ of institutional investors who produce information receive good signals, whereas the remaining fraction $(1 - \lambda)$ receive bad signals; with the complementary probability $(1 - \alpha_H)$ and $(1 - \alpha_L)$, a fraction δ of institutional investors receive good signals, and $(1 - \delta)$ receive bad signals. The model assumes that $\alpha_H > \alpha_L$, and $\lambda > \delta$.

The equilibrium concept used in the model is Perfect Bayesian Equilibrium surviving the Cho-Kreps intuitive criterion. Two kinds of investors exist: institutional investors who can produce information at some cost and retailer investors without information production capacity. The model assumes three possible net demand states in the pre-offer market: high (H), medium (M) and low (L), based on the combinations of demands of two kinds of investors³³.

Two scenarios are set in the model. Under the first scenario, the cost of SEO failure is not too large and firm insiders only need to provide the state-independent discount to induce institutional investors to produce information and consequently bid in the SEO. The expected profit for an institutional investor from trading in the pre-offer market is:

³² Chemmanur and Jiao (2011) set up 4 time spots in the model. Time 3 is the time spot when all cash flows are realised and all information asymmetry is resolved

³³ There are four states, namely high, high-low, low-high, and low. The high-low (low-high) state means the net demand of institutional investors is high (low) and that of noise traders is low(high). For simplicity, Chemmanur and Jiao (2011) impose the parameter restriction and refer to both low-high and high-low as the medium state.

$$\pi_1 = (\theta(\alpha_H\lambda + (1 - \alpha_H)\delta) + (1 - \theta)(\alpha_L\lambda + (1 - \alpha_L)\delta))\pi_1^G + (\theta(\alpha_H(1 - \lambda) + (1 - \alpha_H)(1 - \delta)) + (1 - \theta)(\alpha_L(1 - \lambda) + (1 - \alpha_L)(1 - \delta)))\pi_1^B \quad (3.4)$$

where π_1^G and π_1^B are an institutional investor's expected profit from buying and selling in the pre-offer market respectively.

An institutional investor's expected profit from bidding in the SEO is:

$$\pi_2 = (\theta\alpha_H + (1 - \theta)\alpha_L)\phi_1\pi_2^U + ((\theta\alpha_H + (1 - \theta)\alpha_L)(1 - \phi_1) + (\theta(1 - \alpha_H) + (1 - \theta)(1 - \alpha_L))\phi_1)\pi_2^M + (\theta(1 - \alpha_H) + (1 - \theta)(1 - \alpha_L))(1 - \phi_1)\pi_2^D \quad (3.5)$$

where π_2^U , π_2^M and π_2^D are the expected profits of an institutional investor from bidding in the SEO conditional on the high, medium and low states respectively.

Total profit an institutional investor expects from trading in the pre-offer market and the SEO is:

$$\pi = \pi_1 + \pi_2 \quad (3.6)$$

To induce information production by institutional investors, $\pi \geq c$, where c is the information production cost.

For insiders of the type H firm, the equilibrium payoff is:

$$\begin{aligned}
\pi_H = & \alpha_H \phi_1 (p_2^U q + (m - q)h) + (\alpha_H(1 - \phi_1) + (1 - \alpha_H)\phi_1\phi_2)(p_2^M q + \\
& (m - q)h) + (1 - \alpha_H)(1 - \phi_1)(p_2^D q + (m - q)h) + (1 - \alpha_H)\phi_1(1 - \phi_2)(p_2^M \delta n + \\
& (m - \delta n)h - K)
\end{aligned} \tag{3.7}$$

Similarly, the equilibrium payoff for insiders of type L firm is:

$$\begin{aligned}
\pi_L = & \alpha_L \phi_1 (p_2^U q + (m - q)l) + (\alpha_L(1 - \phi_1) + (1 - \alpha_L)\phi_1\phi_2)(p_2^M q + (m - q)l) + \\
& (1 - \alpha_L)(1 - \phi_1)(p_2^D q + (m - q)l) + (1 - \alpha_L)\phi_1(1 - \phi_2)(p_2^M \delta n + (m - \delta n)l - \\
& K)
\end{aligned} \tag{3.8}$$

where p_2^U , p_2^M and p_2^D represent the SEO offer prices for the high, medium and low states of the pre-offer market respectively, and K is the cost of SEO failure.

In equilibrium, $\pi = c$, and firm insiders adjust the state-independent discount s to induce $n = \frac{q}{\lambda}$ institutional investors. Also, in equilibrium the payoff (π_H and π_L) for firm insiders is maximised. The state-independent discount $s > 0$ and there is no additional state-dependent discount.

Under the second scenario, the cost of SEO failure is sufficiently large. Besides the state-independent discount, firm insiders have to give an additional state-dependent discount for the medium state of the pre-offer market. The additional discount S is set big enough that all institutional investors are induced to produce information and bid in the SEO. Therefore, there is zero probability of SEO failure.

The expected profit for an institutional investor in the second scenario is similar to that in the first scenario. The differences are p_2^M - the SEO offer price for the medium state of the pre-offer market and π_2^M - the expected profit from bidding in the SEO conditional on the medium state. Since there is zero probability of SEO failure, the equilibrium payoff for insiders of the type H firm is:

$$\begin{aligned} \pi_H = & \alpha_H \phi_1 (p_2^U q + (m - q)h) + (\alpha_H (1 - \phi_1) + (1 - \alpha_H) \phi_1) (p_2^M q + (m - q)h) + \\ & (1 - \alpha_H) (1 - \phi_1) (p_2^D q + (m - q)h). \end{aligned} \quad (3.9)$$

Similarly, the equilibrium payoff for insiders of the type L firm is:

$$\begin{aligned} \pi_L = & \alpha_L \phi_1 (p_2^U q + (m - q)l) + (\alpha_L (1 - \phi_1) + (1 - \alpha_L) \phi_1) (p_2^M q + (m - q)l) + \\ & (1 - \alpha_L) (1 - \phi_1) (p_2^D q + (m - q)l). \end{aligned} \quad (3.10)$$

In equilibrium, $\pi = c$ and $n = q$. The state-independent discount s is smaller than in the first scenario. For the medium demand state of the pre-offer market, the firm pays the state-independent discount s and state-dependent discount S . In sum, when the cost of SEO failure K is sufficiently large, the SEO discount is s for the high and low states of net demand and for the medium state it is $s + S$. The state-independent discount $s > 0$ and the additional state-dependent discount $S > 0$.

3.6.2. Empirical Studies on SEO Underpricing

According to the discussions above, most of the theoretical models on IPO/SEO underpricing are based on information asymmetry with various assumptions. However,

the limitation of theoretical models is apparent. That is, the explanation of IPO/SEO underpricing is often developed from one aspect and it is difficult to test the explanation directly. As mentioned in Chapter Two, SEO underpricing has become prevalent from the 1990s onwards. Correspondingly, during the same period, there have been a number of empirical studies on SEO underpricing. Generally, these studies can be categorised into two groups, namely long-run analysis of equity underpricing and determinants of SEO underpricing³⁴.

3.6.2.1. Long-run Analysis of Equity Underpricing

The average underpricing for both IPOs and SEOs has experienced significant changes over the long-run. For instance, Lowry et al. (2010) document that the monthly mean of IPO initial returns for 1965-1980 was 12.1% while it was 25.8% for 1991-2005³⁵. Autore (2011) reports that the SEO mean discounting increased from 0.87% in 1982-1987 to 2.16% in 1988-1993, to 3.03% in 1994-1999 and to 3.20% in 2000-2004. Several studies attempt to give explanations for these changes.

Long-run IPO Underpricing Analysis

Loughran and Ritter (2004) found that IPO average underpricing doubled from 7% during 1980-1989 to almost 15% during 1990-1998. Moreover, the mean underpricing of IPOs reached 65% in 1999-2000 and then reverted to 12% during 2001-2003. The study checked three hypotheses for the change in underpricing: 1) the changing risk composition hypothesis (Ritter, 1984); 2) the realignment of incentives hypothesis

³⁴ This group also includes studies focusing on effects of specific factor(s) on SEO underpricing.

³⁵ Lowry et al (2010) define initial returns as the percentage change from the offer price to the closing price on the 21st day of trading in order to avoid the effects of price support.

(Ljungqvist and Wilhelm, 2003); and 3) the changing issuer objective function hypothesis proposed by Loughran and Ritter (2004). The last of these argues that given the constant level of managerial ownership and other characteristics, issuers became more willing to accept underpricing.

Two reasons are proposed to explain the changing issuer objective function hypothesis. The first reason is that issuers are willing to purchase analyst coverage with excessive underpricing. The second reason is the co-opting of decision-makers through side payments. Specifically, it refers to a practice where underwriters allocate hot IPOs to venture capitalists and the executives of issuing firms. The practice, known as spinning, began in the 1990s and became commonplace by the end of the decade. The empirical results show that 1) a small part of the increase in IPO underpricing can be attributed to the changing risk composition of issuers; 2) there is little support for the realignment of incentives hypothesis; 3) analyst coverage and side payments to CEOs and venture capitalists became of significant importance for underpricing during the internet bubble.

Chambers and Dimson (2009) present a study on UK IPO underpricing over the very long term. The sample has 4540 IPOs on the LSE from 1917 to 2007, and the study divided these IPOs into three subperiods: 1917 to 1945, post-WWII (1946 to 1986) and post-Big Bang (1987 to 2007). Since there was a fundamental change in offer method on the LSE (from the fixed price offer method to the book-building) in the post-Big Bang period, the study concentrates the analysis on the first two subperiods. Thus the multiple regression analysis is based on 2553 IPOs between 1917 and 1986.

Chambers and Dimson (2009) employed four testable hypotheses to explain IPO underpricing, namely *ex ante* uncertainty (Loughran and Ritter, 2004), certification (Carter et al., 1998; Loughran and Ritter, 2004), disclosure and realigned incentives (Sherman and Titman, 2002). The study found that IPO underpricing increased markedly from 3.80% in the pre-WWII period (1917 to 1945) to 9.15% in the post-WWII (1946 to 1986), and the increase in underpricing cannot be explained by the changing risk composition, sector risk, equity market conditions as well as the influence of underwriter reputation and investor protection.

Regarding the increase of IPO underpricing over the first two subperiods, Chambers and Dimson (2009) suggest that other influences overwhelm any benefit from improved post-WWII regulation and disclosure. They argue that the increase of IPO underpricing might be attributed to three explanations. These explanations are the reduced level of trust between investors, issuers and sponsors after the Second World War, the increase of market power of investment banks, and the post-WWII growth of institutional equity investment.

Recently, Lowry et al. (2010) proposed a study focusing on the relationship between the level of IPO initial return and IPO initial return volatility. They suggest that IPO initial return volatility could reflect the difficulty of pricing IPOs, and they found that 1) the IPO initial return volatility fluctuates greatly over time; 2) there is a strong positive correlation between the mean and the volatility of initial returns over time. To explain why the IPO initial return volatility varies over time, Lowry et al. (2010) examined both variation of types of issuers and variation in market-wide conditions.

For certain types of firms (young, small, and technology firms), underwriters might find it is difficult to price their IPOs. When the proportion of these types of firms is higher, IPO initial return variability should also be higher. Lowry et al. (2010) used maximum likelihood estimation (MLE) to estimate the influence of each characteristic on both the level and the uncertainty of firm-level initial returns. Empirical results suggest that when the types of issuers are especially difficult to value, both the mean and the variability of initial returns are relatively high.

To examine whether there are likely to be additional time-series factors, Lowry et al. (2010) used ARMA models (Box et al., 2008) to account for residual autocorrelation and EGARCH models (Nelson, 1991) to account for residual heteroskedasticity. After adding the time-series terms, the coefficients of firm characteristics were still significant with expected signs. Thus, Lowry et al. (2010) conclude that firm characteristics that can be associated with greater uncertainty are reliably associated with higher, and more variable, initial returns.

Moreover, the significance of the time-series parameters also suggests that other factors, such as market-wide conditions, have an important effect on IPO pricing. Lowry et al. (2010) used the NASDAQ time-series return volatility and the NASDAQ cross-section return volatility to capture the two dimensions of the monthly initial returns. Empirical results indicate that NASDAQ time-series return volatility to some extent helps explain the level and volatility of IPO initial returns. There is weak evidence for a positive relationship between average initial returns and the NASDAQ cross-sectional return volatility, and no evidence was found to support an incremental link between the NASDAQ cross-sectional return volatility and initial return volatility.

Long-run SEO Underpricing Analysis

Mola and Loughran (2004) focus on the trend of the increase in SEO discount. They found that three hypotheses, namely changing issuer composition hypothesis, short-selling hypothesis and leaving a good taste hypothesis, cannot fully explain the increasing SEO discount and they emphasise another explanation: increased investment banking power. The changing issuer composition hypothesis refers to the phenomenon that NASDAQ issues increasingly represent the SEO market. This hypothesis is consistent with the variable 'NASDAQ-listed firms' in Altinkilic and Hansen (2003). Because NASDAQ issues often involve greater uncertainty than NYSE/Amex SEOs, more NASDAQ issues result in greater average SEO discounts.

However, data analysis shows that NYSE/Amex SEO discounts also experienced a statistically significant increase during the sample period from 1986-1999. Thus, this hypothesis cannot fully explain why the average SEO discount was increasing. Mola and Loughran (2004) also found little evidence to support the short-selling hypothesis. Leaving a good taste hypothesis means big discounts are given because firms want to come back later for additional funding (Jegadeesh et al., 1993). The paper found that firms with no SEO in the prior year reported larger SEO discounts than firms with an SEO in the prior year, which provides some evidence for the hypothesis.

Moreover, Mola and Loughran (2004) found evidence for increased investment banking power. They examined analyst coverage and the characteristics that determine the subsequent underwriter SEO market share. The study hypothesises that banks use analyst coverage to assist extracting rents from issuers and they document the evidence in market concentration in SEO underwriting industry. Regression results

confirm their argument that analyst coverage is becoming more important. To summarise, Mola and Loughran (2004) claim that they found support for the changing composition and the investment banker power hypotheses. However, as we will discuss thoroughly in Chapter Four, it is highly likely that Mola and Loughran (2004) ignored the problem of offer date correction in SDC database³⁶. Therefore, to what extent this omission might affect their conclusions needs further investigation.

Kim and Shin (2004) examined the trend of SEO underpricing from 1983 to 1998. They argue that the implementation of Rule 10b-21 by the US Securities and Exchange Commission (SEC) on August 25, 1988 led to the increase of SEO underpricing. Their argument is based on theoretical models developed by Parsons and Raviv (1985) and Gerard and Nanda (1993). The implementation of the rule was intended to minimise manipulative short selling prior to SEOs. But Corwin (2003) and Kim and Shin (2004) report that the abnormal negative return even increased after the implementation of Rule 10b-21. The underlining rationale is that the rule actually restricted informational short sales and reduced the informativeness of prices, thereby increasing required underpricing. By introducing a dummy variable, Kim and Shin (2004) proved that the implementation of Rule 10b-21 had positive effects on SEO underpricing³⁷. After exhausting all possible explanations they could find, Kim and Shin (2004) attribute the implementation of Rule 10b-21 to the increase of SEO underpricing.

³⁶ Other studies in SEO underpricing often use volume-based correction methods to deal with the problem of offer date correction (e.g. Corwin 2003; Kim and Shin 2004).

³⁷ The dummy is equal to one if the offer is conducted before the implementation of Rule 10b-21 and zero otherwise.

Autore (2011) proposed three questions against theoretical models supporting the hypothesis that Rule 10b-21 increased SEO discounting: first, the share allocations for manipulative investors are not always guaranteed; second, despite the fact that informativeness could be affected by Rule 10b-21, underwriters can still use information collected in the book-building process to price the offer; third, Rule 10b-21 has less effect on informed short sellers who have negative information than on informed short sellers who have favourable information.

Due to the above concerns, Autore (2011) proposed a new test of the hypothesis that Rule 10b-21 increased SEO discounting. The test is based on the sample of shelf-registered offers. Rule 10b-21 took effect on shelf-registered offers in September 2004 and before that, shelf-registered offers were exempt. The results suggest that the discounting of shelf offers slightly decreases after the regulation takes effects. And Autore (2011) employed a difference-in-difference methodology to rule out the concern that the decrease in discounting is due to a market-wide effect.

The study also re-examines the impact of the adoption of Rule 10b-21 in 1988 using rule-exempt shelf offers as a control group. The study shows that the rule seems to increase discounting in shelf offers by approximately the same amount that it increases discounting in traditional offers. The findings, along with other evidence, suggest that pre-issue short sale constraints do not increase SEO discounting. Moreover, the study argues that a greater prevalence of overnight shelf offers could explain why discounting was greater in the 2000s than in the 1990s. As market participants receive no advanced notice in overnight shelf offers, discounting in overnight offer is, on average, exaggerated compared to other offers.

3.6.2.2. Determinants of SEO underpricing

Two studies present comprehensive analysis on the determinants of SEO underpricing. Altinkilic and Hansen (2003) divided the discounting into expected and surprise components³⁸. In the expected part, their study summarises six variables identified from previous empirical models of expected underpricing in unseasoned offers. These variables are the amount of the offering (Barry et al., 1990; Dunbar, 1995; Hanley, 1993), relative amount (Hansen, 2001), stock return volatility (Barry et al., 1990; Barry et al., 1991; Jegadeesh et al., 1993), stock price (Jegadeesh et al., 1993; Beatty and Welch, 1996), NASDAQ-listed firms and lead bank reputation (Smith, 1986; Booth and Smith, 1986; Carter and Manaster, 1990).

Beside the variables identified in the literature, the model also included the inverse Mills' ratio and other possible variables (industry-specific dummy variables, one for each two-digit SIC code, and dummy variables for each calendar year). Overall, six identified variables and the inverse Mills' ratio were significant and none of the industry and offer-year dummy variable effects were statistically significant. As for the surprise component, the paper argues that offer-day returns are volatile and significantly negatively related to the discount surprise.

Corwin (2003) also used multivariable models to test the determinants of underpricing for SEOs. He selected five determinants in the literature, namely uncertainty and asymmetric information, price pressure, preoffer price moves and manipulative

³⁸ As we will discuss in Chapter Four, the definitions of SEO underpricing are various in the literature. In Altinkilic and Hansen (2003), the discounting is defined as the close-to-offer return which is the same as the definition of SEO underpricing in Corwin (2003).

trading, transaction cost savings and underwriter pricing practices. He found that SEO underpricing is positively related to the level of uncertainty about firm value, but little evidence was found for a reliable relationship between SEO underpricing and proxies for asymmetric information such as firm size and bid-ask spread. Regarding the price pressure, the results suggest that underpricing is positively related to relative offer size, and the effect is most pronounced when the shares have relatively inelastic demand.

As for the manipulative trading hypothesis, Corwin (2003) examined market-adjusted returns prior to the offer. The study uses the bid-ask spread to measure transaction cost savings. As discussed previously, little evidence is found between the variable of bid-ask spread and underpricing. Unlike Altinkilic and Hansen (2003), this study adds the conventional underwriter pricing practices into the analysis. Considering offer price rounding, the study found strong evidence that seasoned offer prices tend to be rounded to even dollar amounts or \$ 0.25 increments. The study also found evidence that the offer price is likely to be set at the closing bid quote for NASDAQ offers and at the closing transaction price for NYSE offers.

Followed the above studies of SEO underpricing determinants, some studies have attempted to add new specific factors to the analysis of SEO underpricing. These studies often focus on the influence of some specific factors. These factors include new proxy of information asymmetry (Chemmanur and Yan, 2009) and the roles of institutional investors (Chemmanur et al., 2009), as well as the role of underwriting syndicates (Jeon and Ligon, 2011; Huang and Zhang, 2011).

Chemmanur and Yan (2009) propose a new way to deal with information asymmetry in equity offerings. They argue that a firm faces asymmetric information in both the product and financial markets. When the firm needs external financing to fund its growth opportunities, the product market advertising is visible to financial markets as well and, in order to convey the product quality and the intrinsic value to customers and investors, the firm uses a combination of product market advertising, equity underpricing and underfinancing³⁹. Under that rationale, they found that product market advertising and equity underpricing are substitutes for a firm issuing new equity. They tested this prediction with a sample of 1517 equity offerings (884 IPOs and 633 SEOs) from 1990 to 2000 and found supporting evidence in the context of firms making IPOs and SEOs⁴⁰.

Another recent study dealing with information asymmetry and the roles of institutions in SEOs is Chemmanur et al. (2009). The study proposes two possible roles for institutions with private information about SEOs, namely a manipulative trading role (e.g. Gerard and Nanda, 1993) and an information production role (e.g. Chemmanur and Jiao, 2011). For the latter role, institutions produce information about issuers and request allocations in SEOs about which they obtain favourable private information.

By using a large sample of transaction-level institutional data, they found evidence for an information production role of institutions instead of a manipulative trading role. Specifically, they found that more pre-offer institutional net buying and larger

³⁹ They refer to underfinancing as raising a smaller amount of external capital than the full information optimum.

⁴⁰ The study required relative data from Compustat. Therefore the sample size is greatly reduced.

institutional allocations are associated with a smaller SEO discount. This result suggests that institutions increase allocations when they have more favourable information about the long-term prospects of the issuers, leading to smaller SEO underpricing. It is worth mentioning that the sample used by Chemmanur et al. (2009) only covers SEOs from 1999 to 2004 and their conclusion does not have direct implications on the increase of SEO underpricing during the past two decades.

Jeon and Ligon (2011) examine the role of co-manager in underwriting syndicates. The study proposes two hypotheses based on the number and characteristics of co-managers. First, the number of co-managers in the syndicate is negatively associated with SEO underpricing. Second, highly reputable underwriters, when they serve as co-managers, may help reduce SEO underpricing. Both hypotheses emphasise the certification roles of underwriters. For the second hypothesis, commercial banks serving as co-managers could use their proprietary information to improve the quality of certification and thus reduce SEO underpricing.

Jeon and Ligon (2011) ran the OLS, 2SLS, and treatment effects regressions. Empirical results show that adding a co-manager significantly reduces underpricing by 0.2% in the OLS while the effect is insignificant after controlling for the endogenous choice of the number of co-managers by using 2SLS. As for the characteristics of co-managers, the results indicate that underpricing decreases by 1.0% and 1.9% by the presence of prestigious co-managers in the OLS and treatment effects regressions. SEO underpricing decreases by about 0.5% when commercial banks are included as co-managers in the syndicate. The above results suggest that effect of the number of co-managers on SEO underpricing is insignificant after controlling for endogeneity of

syndicate structure, and characteristics of co-managers have significant effects on reducing SEO underpricing.

Huang and Zhang (2011) checked the marketing efforts of SEOs by underwriters. The marketing efforts can influence the demand of SEO shares in the primary market and thus lower the offer price discount. Huang and Zhang (2011) used the number of managing underwriters in an SEO syndicate, including lead managers and co-managers, as a proxy of marketing efforts provided by underwriters. They found that the natural logarithm of the number of managers is negatively related to the SEO discount. They also found that the marginal benefits of additional managers are greater when the relative offer size is larger and the stock return volatility is higher. These results are more consistent with the marketing hypothesis than with the information production hypothesis.

Huang and Zhang (2011) also provide further support for the marketing hypothesis by examining the effects of investor networks on SEO discount. They define the variable of investor networks as the number of relationship investors of the co-managing underwriter(s). A relationship investor is defined as an investor that participated in at least 10 SEOs in the 5 years prior to the current SEO, with at least one underwriter in the syndicate being a lead or co-managing underwriter, and a participant is recognised if it has increased its holding of the stock after the SEO. They found that the SEO discount decreases by 0.46% when there is a 1 standard deviation increase in the natural logarithm 1+ the number of co-manager relationship investors. The results provide strong support for the marketing role of investment banks in bookbuilt SEOs.

3.6.3. Explanations for SEO Underpricing

Following on from the discussions above, this section presents a further analysis of several important explanations of SEO underpricing and discounting. We summarise six factors of SEO underpricing for which there is robust evidence in the literature. According to the literature, two factors may have contributed to the increase of SEO underpricing during the past two decades. They are investment banking power and the implementation of Rule 10b-21. In Chapter Five, we will conduct a thorough investigation of these two explanations and possible hypotheses for the increase of SEO underpricing.

3.6.3.1. Information Asymmetry

Information asymmetry seems the most popular explanation in IPO pricing. Loderer et al. (1991) point out that many of the information asymmetry models in IPO pricing can be extended to the case of SEO. However, the results from recent empirical tests suggest that information asymmetry is likely to be a smaller problem for SEO pricing. These studies involve a variety of measures in information asymmetry. For instance, Corwin (2003) measured the information problem by firm size and the bid-ask spread. There is little evidence about a reliable relationship between information asymmetry and these two variables. Huang and Zhang (2011) used the logged pre-issue market capitalisation as a control variable for information asymmetry and found that the market capitalisation parameter is positively related to SEO discount at a statistically significant level.

Altinkilic and Hansen (2003) used three pricing measures to assess whether information during the registration period is incorporated in the discounting. The

results show that expected discounting increases when more positive private information is released during the registration period. Moreover, Liu and Malatesta (2005) used debt ratings as measures of asymmetric information. Their study found that firms with credit ratings are underpriced less and they suggest that credit ratings reduce information asymmetry in equity offerings. To summarise, prior studies suggest information asymmetry is not an important consideration in SEO pricing.

3.6.3.2. Uncertainty about Firm Value

Uncertainty about firm value or price uncertainty is often measured by stock return volatility. Some studies include stock return volatility into the proxies of information asymmetry. For instance, Drucker and Puri (2005) and Altinkilic and Hansen (2000) used stock return volatility to measure information asymmetry. However, Lee and Masulis (2009) point out that stock return volatility is likely to capture other economic effects beyond asymmetric information. That is, stock return volatility can also be used to measure uncertainty and is influenced by industry and economy wide shocks. Therefore, stock return volatility is regarded as a measure of uncertainty in the following discussion.

Corwin (2003) employed stock return volatility as the proxy for price uncertainty. Volatility is defined as the standard deviation of daily stock returns over the 30 trading days ending 11 days prior to the issue. The study suggests that SEO underpricing is positively related to the level of uncertainty about firm value and price uncertainty plays a significant role in SEO pricing. Altinkilic and Hansen (2003) also found strong evidence that stock return volatility is positively related to the SEO discount.

Volatility of secondary market return is widely used as a control variable in recent studies. For instance, Chemmanur et al. (2009) define volatility as the standard deviation of the issuers' stock return during the previous 126 trading days ending 42 trading days before the offering. They found that the volatility was significantly positively related to SEO discount in all regressions. Similarly, Huang and Zhang (2011) define the volatility in the same way as Corwin (2003) and found that volatility was significantly positively associated with SEO discount.

3.6.3.3. Price Pressure

Price pressure refers to the effects of more outstanding shares. The effects can be either permanent or temporary. According to the discussions in Corwin (2003), if the demand curve for the shares of the issuing firm is downward sloping, the increase in supply will result in a permanent decrease in stock price. This is called downward-sloping demand or permanent price pressure. As pointed out by some studies (Scholes, 1972; Mikkelsen and Partch, 1985), a permanent stock price decrease may not take place on the issue day. As for the temporary price pressure, since a seasoned offer brings a temporary liquidity shock, a discount is required to compensate investors for absorbing the additional shares (Corwin, 2003).

Price pressure is often measured by the offer size or relative offer size. Hansen (2001) documents that underpricing increases with the relative amount of IPOs. Altinkilic and Hansen (2003) define relative amount as the gross proceeds with regard to the market value of equity, measured one week before the offer day. They found that discounting is higher for relatively larger amounts. Chemmanur and Jiao (2011) use a similar definition to Altinkilic and Hansen (2003). Although they report a positive

relationship between relative offer size and SEO discount, the coefficients are insignificant.

Corwin (2003) and Huang and Zhang (2011) define relative offer size as the number of shares offered over the total number of shares outstanding before the offer. Both studies report that the relative offer size is significantly positively associated with SEO discount. Corwin (2003) also recorded a significant price drop in the days prior to the offer and a significant price recovery following the offer. Thus, there is little evidence to support permanent price pressure. But the results of the empirical test strongly support the hypothesis that SEO underpricing reflects temporary price pressure.

3.6.3.4. Short-selling and Manipulative Trading

Barclay and Litzenberger (1988) proposed the short-selling hypothesis. Using intraday price data during 1981-1983, they recorded a price pattern, that is, an average 1.5% price decline accompanied by abnormally high trading volume in a short period (15 minutes) after an announcement. The price drop was followed by a significant recovery of 1.5% after the issue day. This provides some evidence for the argument that investors depress stock prices through short-selling to affect the offer price of new equity issues. Moreover, Gerard and Nanda (1993) point out that this manipulative trading might reduce the informativeness of secondary market prices before the offering and force the firm to offer a high discount in order to market its new shares.

Corwin (2003) divides the research period into two parts by the implementation of Rule 10b-21. This study found no evidence that large price drop prior to the offer date

led to more underpricing before Rule 10b-21 was implemented. After the implementation of Rule 10b-21, it records that large price moves in either direction led to more underpricing. Corwin attributes this pattern to the increased short sale restrictions and more uncertainty. This conclusion is also supported by Kim and Shin (2004). They claim that after exhausting all possible explanations, they still found that there was a significant increase of SEO underpricing between the periods before and after the implementation of Rule 10b-21. Therefore, they conclude that the implementation of Rule 10b-21 reduced the informativeness of market prices, leading to more risks and higher SEO underpricing.

However, Mola and Loughran (2004) argue that if manipulative pressures exist, the inefficiency is expected to be eliminated after the offering. They then examined the distributions of P_{T-1} , P_T and P_{T+1} , where P_{T-1} is the prior closing price, P_T is the closing price of the issue day, and P_{T+1} is the day after. These three distributions are quite similar, thus the results of effects of manipulative pressures are mixed in the literature.

3.6.3.5. Price Clustering and Investment Banking Power

Some studies suggest that equity offer pricing is significantly affected by price clustering. That is, offer prices are likely to be set at integers. Lee et al. (1996) document a tendency to set offer prices down to the nearest eighth or integer value. Bradley et al. (2004) found that IPOs priced at integer generate higher first-day returns than those priced on dollar fractions. This might reflect the desire of the underwriter to

reduce the costs of negotiation. Moreover, they argue that clustering at integers is a way to compensate the underwriter for increased uncertainty.

Corwin (2003) tested the effects of price rounding by examining the relationship between underpricing and price level. If price rounding is important, underpricing is expected to be negatively related to price level. The empirical test found strong evidence that offer prices tend to be rounded to even dollar amounts or \$0.25 increments. Mola and Loughran (2004) confirm that SEOs priced at integer have a larger average discount than those priced at fractions. Moreover, their empirical test showed the use of integer offer prices in IPOs increased over time during 1986-1999. IPOs priced at integer had an average first-day return of 21.4% while those priced at fractions had an average first-day return of 8.9%.

In contrast with prior studies, Mola and Loughran (2004) include the clustering of SEO prices as evidence of increased investment banking power. Mola and Loughran add that analyst coverage is an important explanation of increased SEO discounting. Their study also discussed characteristics that determine the subsequent underwriter SEO market share. They document the evidence in market concentration in the SEO underwriting industry. The underlying idea is that big banks have more influential analysts and have more customers in other areas. Firms prefer to choose familiar analysts who will issue favourable and influential reports. As a result, big banks are taking more market shares and have more pricing power in SEOs, but Altinkilic and Hansen (2003) found that the discounting is smaller for issues having a more reputable bank leading the underwriting syndicate.

Price clustering at integer is recognised as an important control variable by a number of studies. For instance, Chemmanur et al. (2009), Jeon and Ligon (2011), Autore (2011) and Huang and Zhang (2011) all include a dummy variable that equals one if an offer is priced at an integer and zero otherwise. The coefficients of this variable are strongly significant in regressions in all of the above studies.

3.6.3.6. NASDAQ-Listed Firms

Firms listed in NASDAQ and NYSE differ in many aspects. For example, NYSE listed firms are often larger and their shares are traded more actively. Corwin (2003) points out that NYSE issues represent a smaller fraction of the existing firm. In his sample, NYSE offered shares took an average 16% of pre-issue shares outstanding while NASDAQ offered shares averaged 26.8% of pre-issue shares outstanding. Altinkilic and Hansen (2003) also included a NASDAQ dummy into their empirical model and conclude that expected SEO discounting is larger for NASDAQ firms. Mola and Loughran (2004) also suggest that NASDAQ-listed issues are associated with greater discounts. In their sample, a NASDAQ dummy was significant through all the sub sample periods.

Recent studies report insignificant influences of the NASDAQ dummy on SEO discount or underpricing. For instance, Jeon and Ligon (2011) found weak evidence that issuers listed on the NASDAQ have higher SEO underpricing than others. Autore (2011) also reports an insignificantly positive relation between the NASDAQ dummy and SEO discount in his sample. Huang and Zhang (2011) used a similar dummy that equals one if issuers are listed on NYSE or AMEX and zero otherwise. They also report that the dummy is insignificantly related to SEO discount.

3.7. Liquidity Shocks, Liquidity and Liquidity Risk

As mentioned in the previous section, one determinant of SEO underpricing-price pressure needs more discussion. As suggested by Corwin (2003), a seasoned offer could be viewed as both permanent price pressure and temporary liquidity shock that must be absorbed by the market. Moreover, Corwin argues that permanent price effects should occur on the announcement day rather than the issue day due to market efficiency. Thus, it is reasonable to refer to the seasoned offer as a temporary liquidity shock to be absorbed by investors. This idea is consistent with Scholes (1972) and Mikkelsen and Partch (1985). Under that rationale, liquidity shocks can be viewed as the extension of price pressure to some extent. In this section, we discuss the differences between liquidity shocks, liquidity and liquidity risk.

In the literature, there are various concepts of liquidity shocks. For instance, studies on mutual funds or hedge funds often regard cash withdrawals or fund inflows as liquidity shocks (e.g. Ding et al., 2009). Studies on liquidity premium refer to a liquidity shock as a sudden drop in wealth or a surprise need for funding (e.g. Huang, 2003). Some studies on liquidity of stock markets assume that liquidity shocks are caused by selling large amounts of assets immediately (e.g. Da and Gao, 2010; Coval and Stafford, 2007). Under this rationale, liquidity shocks can be regarded as a temporary imbalance between supply and demand of the underlying securities. Because this definition is consistent with Corwin (2003), we adopt it.

It is worth distinguishing liquidity shocks, liquidity and liquidity risks. Liquidity can affect the cross-sectional differences of asset return through two channels (Lee, 2011). One is to refer to liquidity as a characteristic. Studies referring to liquidity as a

characteristic investigate the relationship between the expected return and the liquidity of the underlying shares. For instance, Amihud and Mendelson (1986) used the bid-ask spread to measure the liquidity and found that market-observed average return is an increasing function of the spread. Brennan and Subrahmanyam (1996) estimated measures of illiquidity from intraday transaction data. They found a significantly positive relationship between required rates of return and measures of illiquidity after adjusting for the Fama and French risk factors and also after accounting for the effects of stock price level.

Amihud (2002) proposed a novel measure of illiquidity – the average across stocks of the daily ratio of absolute stock return to dollar volume. The advantage of that measure is its availability, since the measure can be easily obtained from daily stock data for long time series in most stock markets. The study shows that expected market illiquidity positively affects ex ante stock excess return. The other channel is to regard liquidity as a risk factor (e.g. Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Liu, 2006; Sadka, 2006; Watanabe and Watanabe, 2008). These studies use market wide liquidity as a state variable that affects expected stock returns.

Liquidity risk cannot be observed directly. For instance, after sorting the portfolio based on the specific liquidity measure, the return difference between the least liquid decile and the most liquid decile remains significant, indicating the possible existence of liquidity premium. If the liquidity premium cannot be explained by the asset pricing model (e.g. CAPM or Fama-French three-factor model), the liquidity premium is shown to exist, and there should then be liquidity risks which are compensated by liquidity premium. In short, liquidity and liquidity risks are related but they are

different terms. Liquidity is used to measure some characteristic of the underlying shares and liquidity risk is the risk caused by market wide liquidity which should be compensated by liquidity premium.

3.8. Immediacy Cost and SEO Underpricing

Butler, Grullon and Weston (2003) investigated the effects of liquidity on investment banks' fees. In their study, they assume that the investment bank's role is similar in spirit to that of the market makers who line up buyers and sellers to facilitate the intermediation process. Therefore, it is reasonable to assume that underwriters face similar inventory risks as market makers do. Chacko et al. (2008) suggest that such inventory risks can be compensated by the immediacy cost and they propose a limit order model which is derived from real options modelling. By developing such a model, they raise the possibility of calculating the immediacy cost accurately at for the first time in the literature. In this section, we introduce the limit order model and discuss its assumptions⁴¹.

3.8.1. Introduction of the Limit Order Model

If the demand flow of an order can be estimated accurately, then the immediacy cost paid by the transaction initiator can be calculated by the limit order model proposed by Chacko et al. (2008). The underlying idea of the model is to incorporate option theory into the transaction cost calculation. That is, a limit order can be viewed as an American call option. In a transaction, the seller of shares (investor) is the option

⁴¹ We attempt to apply the limit order model in SEO pricing. However, the results are not favourable. Detailed discussions are attached in the Appendix 3.

writer and the seller of shares (market maker) is the option owner. The seller can sell the shares through two ways. One is to sell the shares to the market maker; the other is to sell the shares to other investors in the market. However, the opposite flow from other investors arrives stochastically. Therefore, it cannot be regarded as a reliable source for transaction.

If the seller requires an immediate transaction, the seller should set a price much lower than the current price. The buyer can accept this price or wait for the opposing order in the market and so the limit order is effectively an American call for buyer of shares. If the buyer accepts the bid, the buyer indeed takes the option and receives the underlying asset, while the seller sends the option and transfers the underlying asset. The market maker then absorbs these shares and resells them in the market.

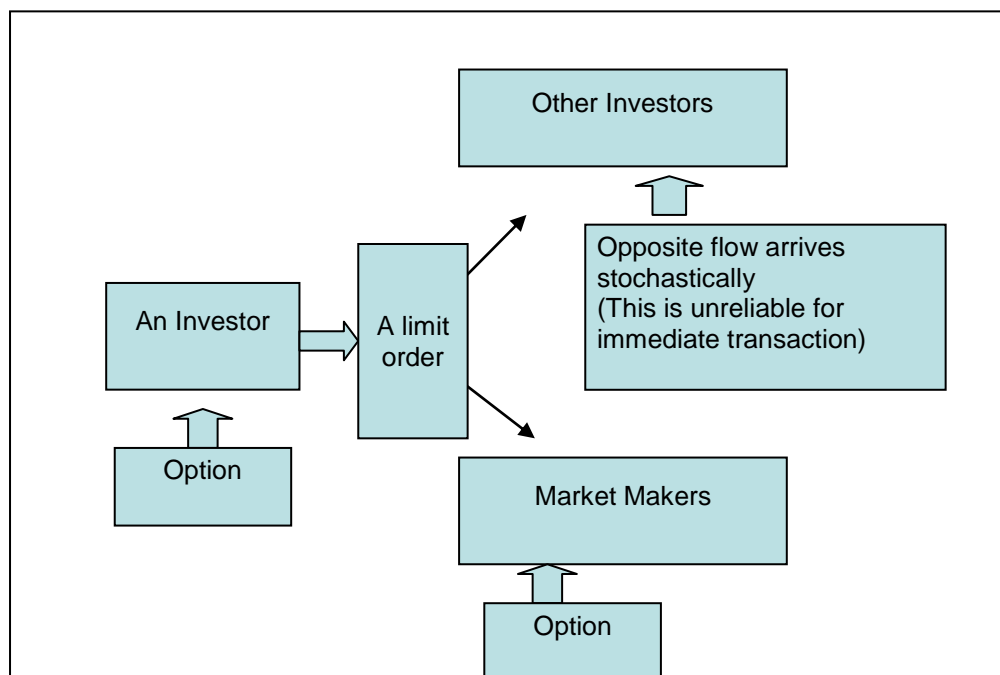


Figure 3-3 Real option in limit order model

In this way, the seller obtains liquidity and the market maker should be rewarded for providing liquidity. At the same time, the seller (option writer) must offer a price at which it is currently optimal for the option owner to exercise the option immediately. If the transaction occurs, the option writer (investor) sells the stock immediately and transfers all the price risk to the buyer. The buyer assumes all the price risk. Because the model is structured through a limit order, it is also called limit order model. This process is illustrated in Figure 3-3.

Table 3-10 Comparison between traditional option and real option in limit order

	Traditional Option	Real Option in Limit Order
Underlying Asset	Shares or Other Financial Assets	Shares
The Option Type	American Call In/At/Out the Money	American Call In the Money
The Option Writer	Sell the option, receive the premium (option price) and assume the upward price risk	Investors send the option, and assume the upward price risk
The Option Owner	Buy the option, pay the premium (option price) and hedge the upward price risk	Market Maker receive the option, and hedge the upward price risk
Period	Different time period (e.g. 3 months, 6 months)	Immediacy
At exercise time, the Option Owner	Receive the payoff from the option writer if option is exercised, loss premium if option is yet exercised	Take and Exercise option at the same time. Receive the underlying asset and pay discounted price (strike price).
At exercise time, the Option Writer	Assume the loss if option exercised, obtain the premium if option is yet exercised.	Send and exercise option and receive at the same time. Transfer underlying asset and receive discount price (strike price).

3.8.2. Comparison between Traditional Option and Real Option in Limit Order

In Table 3-10, a comparison is made between a straightforward option and real option in limit order. The most obvious difference is the time period of the option. The real option in limit order requires immediate exercise. The difference arises due to the different roles between two kinds of options. Plain options are used to hedge risk, while the real option in limit order is mainly use to provide liquidity for the seller. For plain options, size or volume is not a pricing factor. However, for the limit order model, offer size and arrival rate of opposing order are critical for pricing.

3.8.3. Assumptions of Limit Order Model

The limit order model has several assumptions that need to be considered in order to apply it in this study. First of all, it requires a price-driven market structure. A price-driven market is a market where market makers maintain an inventory of securities and continuously quote prices at which they will buy (the bid price) and sell (the ask price). Customers choose the best price quotes, and the competition among the market makers promotes the best price. The US NASDAQ is a price-driven market. The NYSE, the biggest market in the world, is a combination of an order-driven and price-driven system. The monopolist position provides a market maker the privilege of meeting the limit order at the first time. Although the option is available to both the market maker and opposing order flow, only the market maker can be regarded as a reliable source to supply immediacy at any given time because opposing order flow arrives stochastically.

The second assumption is that the opposing order arrival rate is stochastic. In other words, the study does not assume time-varying arrival rate. The instantaneous probability of observing a Q -share buy (sell) imbalance during the next instant is given by $\lambda(Q)dt$. The arrival rate of opposing order flow is a function of the order quantity Q . In particular, it applies a simple assumption about arrival rate. That is, the expected waiting time for the completion of a Q -share order is precisely Q times larger than the corresponding waiting time for a one-share order. This is a relatively strong assumption but can bring advantages in model estimation.

The third assumption is the impatience of the trader initiator. This assumption is critical for the model. When a seller has no patience in the transaction, the biggest discount is given to ensure an immediate transaction. Moreover, Chacko et al. (2008) point out that only when zero patience is assumed can the model give analytic results. The assumption of impatience also implies the “one-shot execution”. That is, it is not possible for a limit order to be filled by a sequence of partial fills. This simplification also facilitates the calibration of the mean inter-arrival time of opposing orders.

The final assumption is that the limit order writer cannot cancel the limit orders. Due to this assumption, the option becomes perpetual. Cancellation occurs when the limit order is filled by the opposing order. This seems a demanding assumption, however, it also brings the advantage of generating analytic results.

3.8.4. Model Discussion

The limit order model⁴² depends on three factors: (1) market structure; (2) arrival rate of opposing order; (3) the evolution of the fundamental value. Because these factors have complex dynamics in reality, the limit order model is constructed in a reduced-form. The model gives the percentage immediacy cost as follows:

$$p(Q) = \frac{K_B(Q, \alpha = 0) - V_t}{V_t} = -\frac{1}{\phi_+(\lambda^B)}, \quad (3.11)$$

where V_t is the fundamental value of the shares, $K_B(Q, \alpha = 0)$ is the bid price for the Q shares when sellers has zero impatience

$$\phi_+(\lambda^B) = \left(\frac{1}{2} - \frac{r}{\sigma^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r}{\sigma^2}\right)^2 + \frac{2(r + \lambda^B(Q))}{\sigma^2}}, \quad (3.12)$$

where r is the risk free rate, σ is stock return volatility, $\lambda^B(Q)$ is the opposing arrival rate for Q shares.

According to the second assumption, $\lambda^B(Q) = \lambda^B(1) \cdot Q^{-1}$ (the expected waiting time for the completion of a Q -share order is precisely Q times larger than the corresponding waiting time for a one-share order). In particular, whenever:

$$\lambda^B(Q) \gg r, \quad \phi_+(\lambda^B) \approx \frac{\sqrt{2\lambda^B(Q)}}{\sigma}.$$

⁴² The derivation of the model is given in Appendix 3.

$$\text{So the percentage immediacy cost } p(Q) \approx \sigma \sqrt{\frac{Q}{2\lambda^B(1)}}. \quad (3.13)$$

This approximate formula illustrates the relationship between immediacy cost and those variables. The bid-ask spreads increase with the volatility of the underlying shares. Larger transactions (larger Q) effectively require the immediacy demander to write longer maturity and therefore more valuable options, which translates into greater transaction costs. In particular, when order flow arrives at an infinite rate, the liquidity in the market is infinite. The monopolist position of the market maker collapses and the price of immediacy is zero for any quantities. All these predictions could find some support from empirical evidence.

CHAPTER 4: DATA AND SAMPLE DESCRIPTION

In this chapter, the data used in this thesis are discussed. Because sampling procedures have important effects on the results, the sampling procedures employed in several studies are discussed first, and then the sampling procedures of this study are proposed. After that, the offer date correction problem in the SDC data base is discussed, and then the differences in the concept of underpricing among various studies are discussed. Finally, descriptive statistics are presented.

4.1. Sampling Procedures used by Several Important Studies

As discussed in Chapter Two, this study focuses on seasoned equity offerings in the US market. There are some differences in the sample selections made by several important studies on SEO underpricing (discount) in the US market. In this section, these differences are presented, and then the possible impacts on results are discussed.

Mola and Loughran (2004) used a sample of 4,814 US SEOs from the period 1986-1999.⁴³ Their sample selection began with all common stock seasoned equity offerings by US operating companies from January 1986 to December 1999 provided by the Securities Data Company (SDC)⁴⁴, then closed-end investment funds, real estate investment trusts (REITs) and unit investment trusts, beneficial interests, limited

⁴³ In the regression analysis, only 4,417 US SEOs were available due to the missing data for some variables.

⁴⁴ The database is also referred to as SDC Platinum in some studies.

partnership and American Depository Receipts (ADRs), rights and unit issues were excluded.

As discussed in Chapter Two, closed-end investment funds and real estate investment trusts (REITs) and unit investment trusts are different from the common offerings and the deletion is reasonable. As for ADRs, they are often issued by foreign companies. Due to the differences in regulations and operational environments between countries, ADRs are often excluded from the sample. Rights issues are exclusive to the existing shareholders, which is different from the common issues that any investors in the market can buy. Therefore, it is reasonable to exclude rights issues from the sample. Since unit issues are a combination of different classes of shares, the pricing mechanism is also different from common shares.

After excluding the above types of equity offerings, the sample is further constrained on offerings made by firms listed on the NYSE, Amex, or NASDAQ. In other words, the offerings issued on the OTC markets and small exchanges in the US are excluded⁴⁵. The reason for this exclusion is that shares traded in those markets are often less liquid than the major markets and the issuer qualities are often low. These characteristics could affect the pricing of the offerings. Finally, due to missing SDC closing prices on the day before the issue, 222 offerings are excluded.

The sample selected by Mola and Loughran (2004) contained a large number of offerings. However, two points remain unclear about the selection. First, primary

⁴⁵ Those small exchanges include, for instance, the Boston and Chicago Exchange.

stock offerings and combination primary-secondary stock offerings, and pure secondary stock offerings are all included in the sample. As discussed in Chapter Two, pure secondary stock offerings do not bring any cash for the issuing firm⁴⁶. This sort of offering does not serve the purpose of raising capital. Many studies into SEOs (e.g., Corwin, 2003; Kim and Shin, 2004) exclude pure secondary stock offerings due to this consideration. Second, the study does not mention whether data from the Center for Research in Security Prices (CRSP) data were used. In the SDC database, trading information for the shares, such as price, volume, bid, and ask price, is only available on the issue day or not available at all. It is impossible to calculate some important variables, such as volatility and bid-ask spread. More importantly, as will be discussed in Section 4.4., without daily trading information it is difficult to identify the uncorrected issue dates in the SDC database.

Corwin (2003) began his sample selection with the full sample of US common stock offerings from January 1st 1980 to December 31st 1998. He excluded IPOs, units, rights, mutual conversions, and issues by non-US firms, closed-end funds and utilities. The criteria are similar to those of Mola and Loughran (2004). However, Mola and Loughran included utilities in their sample. Other studies, for example Altinkilic and Hansen (2003), did not include utilities. After the above selection, Corwin (2003) obtained additional data from the CRSP. In that database, the daily trading information (such as price, volume and SIC code) about the shares of the issuing firm is available.

⁴⁶ Bortolotti et al. (2008) note that most empirical studies screen out pure secondary offers due to either deliberate choice (to examine only shares issued by firms) or an inherent objective of examining capital-raising choices (as in studies of rights offerings or shelf registrations).

Corwin excluded issues that had fewer than 30 days of trading data prior to the offer on CRSP. He screened out all pure secondary offers and only considered offerings with shares listed on the NYSE and NASDAQ. Offerings with an offer price less than \$3.00 and more than \$400.00 were excluded from the sample. Due to the need to investigate the effects of cumulative market-adjusted returns (CAR) on SEO underpricing, the offers for which a stock split occurred during the 11-day window surrounding the offer date were excluded. Moreover, Corwin (2003) pointed out the possible data mistakes made by SDC and proposed a method to deal with outliers. In the sample, issues with underpricing of more than 60% were regarded as outliers. This method is also adopted by Bowen et al. (2008), who excluded offers with absolute value of underpricing more than 50%.

Altinkilic and Hansen (2003) collected two samples of SEOs. One sample included SEOs from 1990 to 1997 and the other, SEOs from 1980-1984. The criteria of sample selection were the same for both samples. Only firm-underwritten, syndicated offers were included. They included utility firms but excluded all regulated firms and financial firms⁴⁷. They also excluded shelf offers and offers that had warrant, and unit offers. Small issues with proceeds under \$10 million were excluded from the sample. Altinkilic and Hansen (2003) also collected daily transaction data from CRSP. However, the study does not mention whether their sample excluded pure secondary offerings or offerings made by non-US firms (their first sample contained 1703 offerings).

⁴⁷ In their sample, regulated firms are defined as SIC codes equal to 400s and financial firms are defined as SIC codes equal to 600s.

Kim and Shin (2004) used a sample of 3304 SEOs from 1983 to 1998. The starting point was chosen as 1983 because SEC filing dates are only reported for offerings since 1983. In their sample, IPOs, right issues, unit offerings, simultaneous international offerings, shelf-registered offerings, and offerings made by private firms, financial firms and utilities firms were excluded. It is worth mentioning that they included offerings that filed one of three registration forms. As a result, the final sample only contains SEOs issued to the public for external financing.

Jeon and Ligon (2011) selected the sample based on all completed SEOs and withdrawn SEOs from 1997 through 2007. They screened out non-US firms, REITs, limited partnership, units, ADRs, rights offerings, pure secondary offers, offers by firms not listed on NYSE, AMEX, or NASDAQ, offers with an offer price of less than \$3 or greater than \$ 400, offers by financial and utility firms, and offers without price and financial data in CRSP and COMPUSTAT. The final sample has 2071 completed and 183 withdrawn SEOs.

In Huang and Zhang (2011), the sample contains 3000 US SEOs from January 1995 to December 2004. In the initial screening, they excluded rights, REITs, units, limited partnerships, mutual conversions, spinoffs, ADRs, closed-end funds, pure secondary offers and offers with no link to the CRSP database. They then screened out offers without gross spread or total number of shares offered, offers with an offer price of less than \$3 or greater than \$400, offers without relative CRSP data, CDA Spectrum

(13f) data and IBES data⁴⁸. Regarding the offer day correction, Huang and Zhang (2011) follow the correction method in the literature (e.g. Altinkilic and Hansen, 2003; Corwin, 2003).

In sum, most SEO studies exclude pure secondary offerings and issues made by non-US firms. Often issues in the OTC market or from private firms are excluded due to their different characteristics (low liquidity or high risk). Also often excluded are unit offerings and rights offerings. All these exclusions make the samples from different studies more comparable. It is worth mentioning that some studies completely exclude issues made by financial firms while some include the majority of issues made by financial firms. The complete exclusion of issues from financial firms suggests that those studies focus on capital-raising choices. However, the exclusion also reduces the sample size and might ignore the possible impacts on the SEO market made by offerings of financial firms. Some studies exclude utility offerings. Including utility offerings keeps up the sample size and it is also possible to identify their effects by adding dummy variables in the analysis⁴⁹.

4.2. Sample Selection

In this thesis, two samples are selected. Sample 1 is selected by following the procedures used by Corwin (2003). Sample 2 is selected using the criteria set by Mola and Loughran (2004). Sample 1 is mainly used to investigate the possible explanations

⁴⁸ Both the CDA Spectrum (13f) and the IBES recommendation database are products from Thomson Financial. The CDA Spectrum (13f) provides data of institutional ownership and the IBES provides analyst recommendations for each SEO.

⁴⁹ For instance, Mola and Loughran (2004) included utility offerings and added a utility dummy in their analysis.

for SEO underpricing proposed in this thesis (and covers a longer time span than the other). The second sample is mainly employed to check the investment banking power hypothesis made by Mola and Loughran (2004). As discussed in Chapter Two, the hypothesis is supported by evidence drawn from a database without offer date correction, therefore a thorough investigation is needed. Both offer dates in Sample 1 and Sample 2 are adjusted based on the methods discussed in Section 4.4..

4.2.1. Sample 1

The sample selection uses procedures similar to those used by Corwin (2003). This sample is also used in the next chapter for the analysis of the Rule 10b-21 hypothesis because Kim and Shin (2004) used a similar sample selection procedure to Corwin (2003). The data include all common stock seasoned equity offerings by US companies occurring between January 1987 and December 2009 provided by the SDC. We obtained a total of 11,183 SEOs. The following restrictions are imposed on the sample:

1. Rights and issues from mutual conversions, closed-end funds and REITs are excluded⁵⁰.
2. Only US issues are included in the sample⁵¹.
3. The issues should include at least some primary shares and the issuing firm must be traded on the NYSE or NASDAQ.

⁵⁰ Rights are defined as issues with OFFERTECH in SDC labelled as “RIGHTS”. Issues from mutual conversions, closed-end funds and REITs are defined as offerings with SIC code equal to 6978 and 6726.

⁵¹ Issues with Nation labelled as “United States” in SDC are kept.

4. Only common shares, class A shares and class B shares are included in the sample⁵². These issues should have at least 30 days of trading data prior to the offer from CRSP.
5. Issues should have an offer price of at least \$3.00 and less than \$400.
6. Exclude offers where stock split occurred during the 11-day window surrounding the offer date.
7. To avoid possible data errors in the SDC database, 1% extreme value (the highest 0.05% and the lowest 0.05%) of SEO discounts are excluded from the sample.

Therefore, Sample 1 includes 5347 SEOs from 1987 to 2009. To facilitate further analyses, we divide the sample into three subperiods, namely 1987-1995, 1996-2001 and 2002-2009. Each subsample has similar numbers of observations after considering missing data for some issues.

4.2.2. Sample 2

Sample 2 is a replication of the sample in Mola and Loughran (2004). However, in order to adjust offer dates stated by SDC, the sample requires data from CRSP. Therefore, there are some slight differences between Sample 2 and the original sample in Mola and Loughran (2004). We collected 6719 seasoned equity offerings in the SDC all US Public New Issues from January 1st 1986 to December 31st 1999. The following sample selection procedures are implemented to obtain Sample 2:

⁵² This restriction deletes those uncommon types of shares (such as Class A/B Sub Voting Shares) which compose a small portion of the whole sample.

1. Rights and issues from closed-end investment funds and real estate investment trust are excluded.
2. Only common shares, class A shares and class B shares are included in the sample. The issues should have at least 30 days of trading data prior to the offer from CRSP because the offer day correction requires trading data from CRSP.
3. The issuing firm must be traded on the NYSE, Amex or NASDAQ.
4. The issues with the missing prior closing price are also deleted. To avoid possible data errors in the SDC database, issues with the absolute value of SEO discounts defined by Mola and Loughran (2004) of more than 50% are deleted. The issues with the missing prior closing price are also deleted.

Sample 2 includes 4419 SEO issues from the period 1986-1999.

4.2.3. Additional Data for Both Samples

Besides the sample selection, we also collected data from three other sources. Daily stock prices, trading volume, the number of shares outstanding, closing bid and ask prices were collected from CRSP. We did not have access to the intra-day transaction data which can be collected from NYSE's Trades and Quotes (TAQ) database. Corwin (2003) collected intraday and closing quote data from this database - but the data in TAQ are only available from January 1st 1993. We used the closing bid and ask prices collected from CRSP instead. Therefore, our closing quote data had a longer time span than those of Corwin (2003). We also collected the underwriter rankings from Ritter's website <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. As for the Top-tier analyst

ranking used by Mola and Loughran (2004), we collected the ranking information from the magazine *Institutional Investor*.

4.3. Clarification of SEO Underpricing and Discount

It is important to distinguish the concept of SEO underpricing from that of IPO underpricing. There is a clearly unified measure of IPO underpricing – the difference between the offer price and the closing price at first trading day divided by the offer price. However, this is not the case in the SEO studies, where the underpricing actually has two different definitions. One is close-to-offer return, the other offer-to-close return. Close-to-offer return is measured as the ratio of the offer price to the pre-offer close minus one⁵³. In this section, we follow the definition proposed by Kim and Shin (2004) and call close-to-offer return underpricing (R0).

$$\text{Close-to-Offer Return: } \textit{underpricing} (R0) = \frac{\text{Prior Closing Price} - \text{Offer Price}}{\text{Prior Closing Price}}$$

Some studies of SEO underpricing take close-to-offer return to define the underpricing (e.g. Kim and Shin, 2004; Corwin, 2003; Bowen et al., 2008). The reason is that, for seasoned equity offerings, the prior closing price on the secondary market already provides a benchmark and adjustment may be made based on that price. As a result, this measure is consistent with the pricing practice in an SEO transaction. Close-to-offer return is also called SEO discount in some studies (e.g. Autore, 2011; Huang and

⁵³ Many studies times this ratio by negative one to make it positive and more comparable with underpricing (R1)

Zhang, 2011) in order to distinguish close-to-offer return underpricing from offer-to-close return underpricing.

Offer-to-close return is defined as the ratio of a closing price on the issue day to the offer price, minus one. We call offer-to-close return underpricing (R1).

$$\text{Offer-to-Close Return: } \textit{underpricing} (R1) = \frac{\text{Closing Price on the Issue day} - \text{Offer Price}}{\text{Offer Price}}$$

Several studies of SEO underpricing take offer-to-close return as underpricing (Altinkilic and Hansen, 2003; Kim and Park, 2005; Bortolotti et al., 2008; Jeon and Ligon, 2011)⁵⁴. They argue that this definition can provide relevant evidence to compare the underpricing of SEOs and IPOs. Some studies have already proven that differences in underpricing definition may have non-substantial impacts on the conclusion⁵⁵.

The difference between the definitions of underpricing may cause ambiguity. In this thesis, we follow the definition used by Corwin (2003) and refer to SEO underpricing as the close-to-offer return (underpricing (R0) or SEO discount). The empirical models in Chapters Six and Seven are developed specifically for the underpricing defined by the close-to-offer return (or SEO discount).

⁵⁴ Altinkilic and Hansen (2003) define underpricing as the logarithm of the ratio of the offer-day close to the offer price and discounting as the logarithm of the ratio of the close price prior to the offering to the offer price. These definitions are qualitatively the same as R0 and R1.

⁵⁵ For instance Kim and Park (2004) use the sensitivity analyses to prove that the conclusion base on R(1) can also hold for R(0).

Mola and Loughran (2004) define SEO discount as:

$$SEO\ Discount\ (SDC) = \frac{Prior\ Closing\ Price - Offer\ Price}{Offer\ Price}$$

We call this definition Discount (SDC) because this discount is provided by the SDC directly as “Percent Change Stock Price 1 Day Before Offer to Offer Price” (PCT1DAYBEF)⁵⁶. This definition is different from both R(0) and R(1) but is closer to R(0). Both R(0) and Discount (SDC) involve the closing price prior to the issue. Therefore, R(0) and Discount (SDC) are analogous. In Chapter Five, the discussion for the investment banking hypothesis is based on Discount (SDC).

4.4. Offer Date Correction

Almost all studies in SEO underpricing point out the necessity of offer date corrections in the SDC database. Lease, Masulis, and Page (1991) discovered that offer dates reported by the SDC database are often inappropriate for analysing price effects because some offers that take place after the close of trading are recorded as taking place on that day. These offers should be recorded as taking place on the day after the stated offer dates. After examining time stamps from the Dow Jones News Service (DJNS), they found that 25% of offers from 1981 to 1983 took place after the close. Eckbo and Masulis (1992) also found that 20% of offers from 1963 to 1981 took place after the close. They used the offer prospect date to identify the offer date. The last sales price is the share’s closing price on the date recorded on the prospectus.

⁵⁶ This definition is calculated as ((PR1DB – USPR) / USPR)*100. USPR is the offer price and PR1DB is the prior closing price. It is only applied to secondary common stock issues.

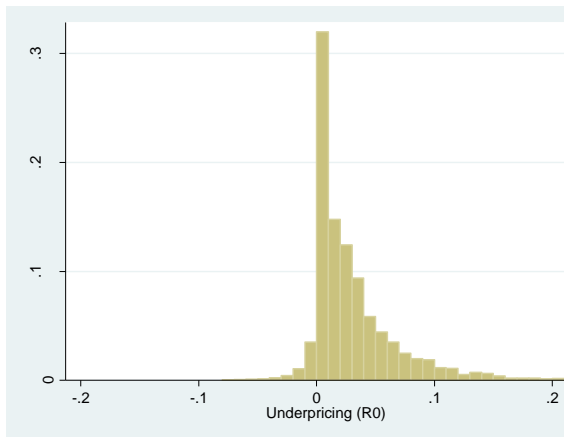
If the date coincides with the prospectus date, then the offer date should be recorded as the following day. Eckbo and Masulis began to use DJNS to identify the offer dates for issues that occurred from 1980 onward.

Chemmanur, He and Hu (2009) used Factiva, a comprehensive business news archive service, to identify the correct offer dates and found that about 70% of Factiva offer dates differ from SDC offer dates between 1999 and 2004. Safieddine and Wilhelm (1996) further note that even time stamps from the DJNS may not identify the true offer dates. To deal with the problem, they applied a volume-based correction method. Following Safieddine and Wilhelm (1996), Corwin (2003), Kim and Shin (2004), Kim and Park (2005) and Huang and Zhang (2011) all applied a volume-based offer date correction in their studies⁵⁷.

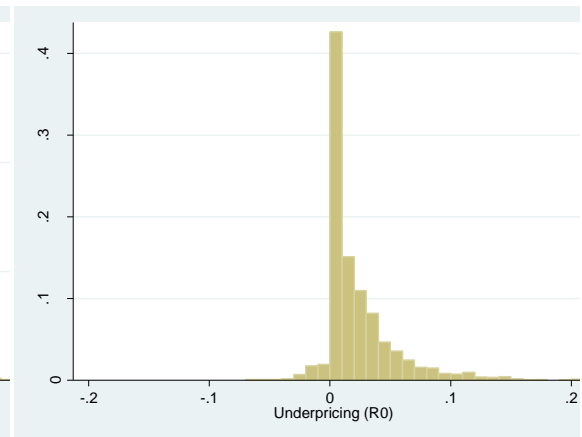
In this thesis, we follow the volume-based correction method. If the trading volume on the following day is (1) more than twice the trading volume on the reported SDC offer date and (2) more than twice the average daily volume over the previous 250 trading days, then the day following the SDC offer day is chosen as the offer date; otherwise, the reported offer date is used. The accuracy of the volume-based correction method is confirmed by Altinkilic and Hansen (2003). They checked the time stamps from DJNS and compared the dates with those obtained from the volume-based correction method. In their sample, the two procedures identified the same offer day for 98% of all the issues. In the sample of this thesis, 53.6% of offer dates are changed under the volume-based correction method.

⁵⁷ Kim and Shin (2004) determined the offer date by checking only whether the trading volume on the following day is more than twice the trading volume on the reported SDC offer date.

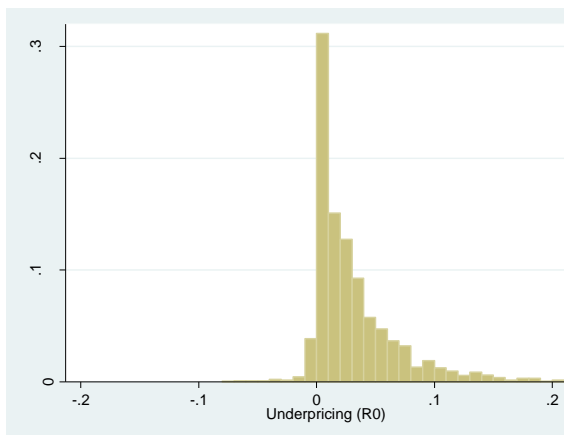
4.5. Descriptive Statistics



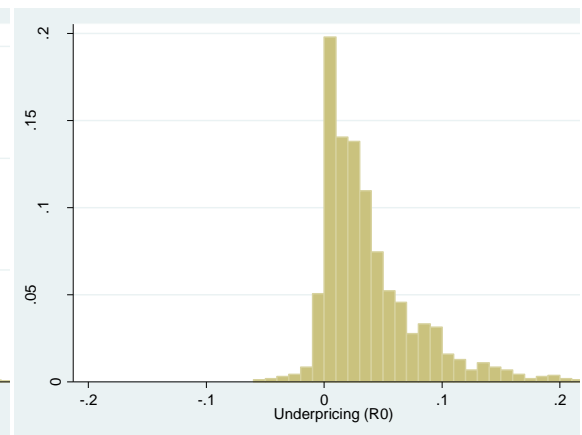
Panel A Rate of Underpricing (R0) From 1987-
2009



Panel B Rate of Underpricing (R0) From 1987-
1995



Panel C Rate of Underpricing (R0) From 1996-
2001



Panel D Rate of Underpricing (R0) From 2002-
2009

Figure 4-1 Panels of magnitudes of SEO underpricing (R0)

Table 4-1 Descriptive statistics of underpricing R(0) and underpricing R(1)

Year	No. of Obs.	Mean of R(0)	Median of R(0)	Mean of R(1)	Median of R(1)
1987	172	0.0090	0.0000	0.0090	0.0025
1988	70	0.0083	0.0000	0.0113	0.0000
1989	128	0.0126	0.0052	0.0148	0.0000
1990	102	0.0139	0.0064	0.0137	0.0014
1991	297	0.0205	0.0097	0.0194	0.0082
1992	274	0.0238	0.0127	0.0230	0.0098
1993	384	0.0249	0.0137	0.0224	0.0094
1994	216	0.0244	0.0159	0.0274	0.0150
1995	349	0.0275	0.0184	0.0261	0.0137
1996	402	0.0342	0.0200	0.0348	0.0152
1997	356	0.0279	0.0192	0.0282	0.0132
1998	223	0.0225	0.0130	0.0237	0.0119
1999	267	0.0269	0.0163	0.0312	0.0118
2000	279	0.0314	0.0209	0.0444	0.0150
2001	207	0.0363	0.0237	0.0418	0.0265
2002	192	0.0329	0.0263	0.0290	0.0216
2003	219	0.0319	0.0215	0.0395	0.0210
2004	242	0.0273	0.0201	0.0281	0.0130
2005	189	0.0299	0.0208	0.0290	0.0129
2006	180	0.0317	0.0222	0.0298	0.0184
2007	154	0.0277	0.0215	0.0229	0.0080
2008	130	0.0489	0.0348	0.0436	0.0133
2009	315	0.0599	0.0491	0.0441	0.0264
Period1 1987-1995	1,992	0.0212	0.0112	0.0207	0.0084
Period2 1996-2001	1,734	0.0301	0.0192	0.0339	0.0147
Period3 2002-2009	1,621	0.0375	0.0263	0.0339	0.0171
p-value for diff(2)-(1)		0.0000	0.0000	0.0000	0.0000
p-value for diff(3)-(2)		0.0000	0.0000	0.4950	0.4099
Underpricing R(0) is defined as $((P-OP)/P)*100$, where P is the prior offer closing price and OP is the offer price. Underpricing R(1) is defined as $((P1-OP)/OP)*100$, where P1 is the closing price on the issue day and OP is the offer price. p-values for difference within subsample means (medians) are from standard t-tests (Wilcoxon rank-sum test)					

There are 5347 SEOs in Sample 1, all from the period 1987 to 2009. The descriptive statistics are based on this sample of 5347 SEOs. Because some variables are missing for some SEOs, these SEOs are excluded from the regression analysis, reducing the sample size to 4756⁵⁸. However, we replicate descriptive statistics for this reduced-size sample and find all the conclusions drawn for the full sample still hold for the reduced sample. The figure and table of descriptive statistics for the reduced sample are presented in Appendix 4 and 5.

According to Figure 4-1, Panel A reflects a skewed distribution of SEO underpricing (R_0). Clearly, an SEO is more likely to be discounted than overpriced. Panel B in the first period shows more than 40% of SEOs in the first period are discounted at 1% or less and fewer than 20% of SEOs are discounted at 1% to 2%. However, Panel C and Panel D show the trend of increase in SEO underpricing (R_0). In the second period, the percentage of SEOs with 1% or less underpricing (R_0) declines to around 30%. In the third period, the percentage of SEOs with 1% or less underpricing (R_0) further declines to below 20%. These panels clearly show the increase of SEO underpricing (R_0) over the sample period from 1987 to 2009.

Table 4-1, Figure 4-2 and Figure 4-3 further confirm the increase of SEO underpricing in the sample period. All p-values for difference within subsample means (medians) are statistically significant for underpricing (R_0). These results provide solid evidence for the increase in SEO underpricing during the past two decades. However, the pattern of SEO underpricing (R_1) is slightly different from underpricing (R_0). For

⁵⁸ Those missing variables are closing bid and ask price, number of shares outstanding from CRSP and gross spread from SDC.

underpricing (R1), there is no statistically significant increase from Period 2 to Period 3. Only the increase in R(1) from Period 1 to Period 2 is reported as statistically significant.

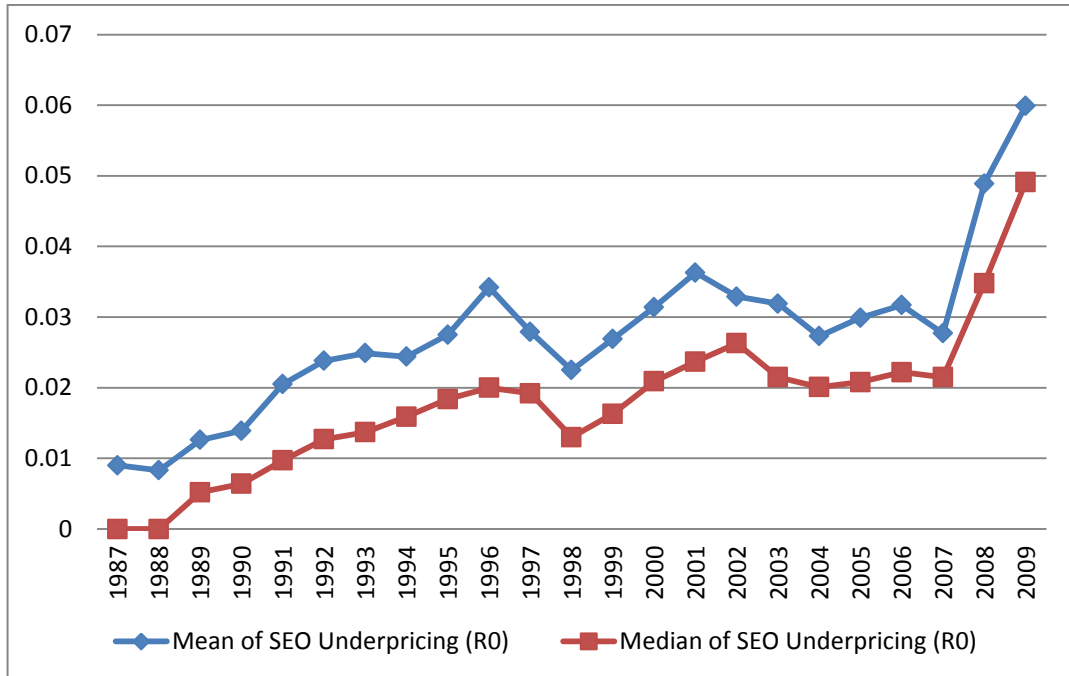


Figure 4-2 Mean and median of SEO underpricing (R0)

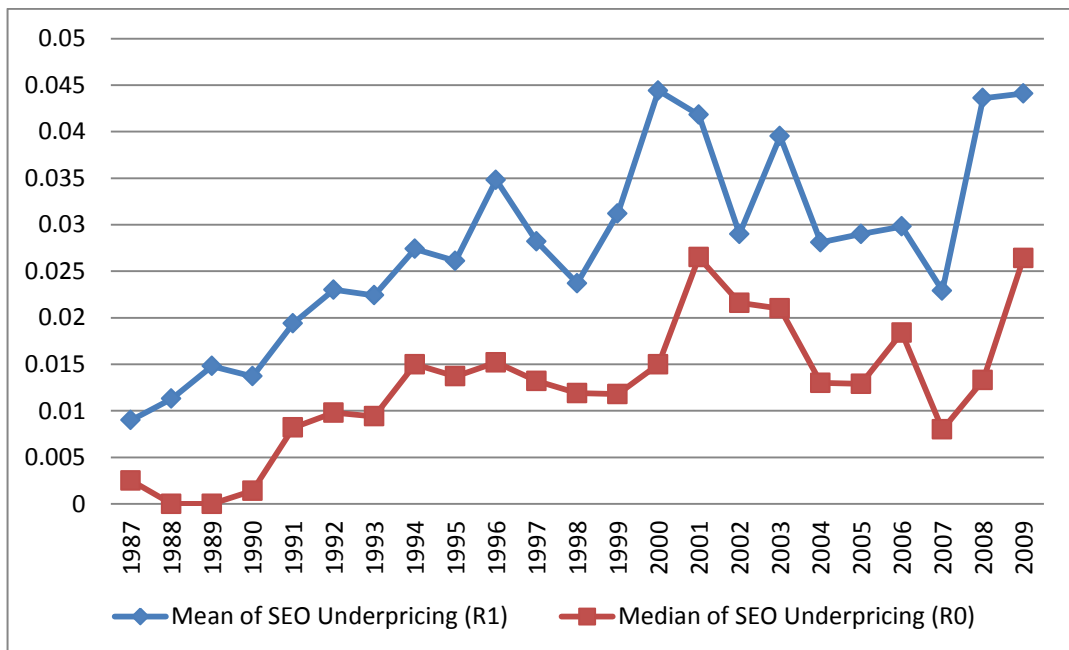


Figure 4-3 Mean and median of SEO underpricing (R1)

CHAPTER 5: EXPLANATIONS FOR THE INCREASE OF SEO UNDERPRICING

In this chapter several important existing explanations for the increase of SEO underpricing are thoroughly discussed and re-examined. These explanations are the hypothesis of Rule 10b-21 (Kim and Shin, 2004), the hypothesis of investment banking power (Mola and Loughran, 2004), the changing issuer composition hypothesis (Loughran and Ritter, 2004; Mola and Loughran, 2004) and leaving a good taste hypothesis (Jegadeesh et al., 1993). The hypothesis of Rule 10b-21 is tested using the first sample selected in Chapter Four, while the other hypotheses are tested using the second sample in Chapter Four, which follows the sampling procedures of Mola and Loughran (2004).

5.1. Implementation of Rule 10b-21 Hypothesis

Kim and Shin (2004) argue that the implementation of Rule 10b-21 by the US Securities and Exchange Commission (SEC) on August 25, 1988 is the reason for the increase of SEO underpricing. Before the implementation of the rule, there were significant temporary price declines in the days prior to seasoned offers. Therefore, the rule is supposed to minimise price manipulation by imposing restraints on the covering of short sales using shares obtained from seasoned equity offerings⁵⁹.

⁵⁹ In 1997, the Securities and Exchange Commission (SEC) replaced Rule 10b-21 with Rule 105 of Regulation M, under which the restricted period is limited to the five business days prior to the offering. Since then, the restraint falls under Rule 105 of Regulation M. For simplicity, the rule is referred to as Rule 10b-21 throughout the thesis.

5.1.1. Underlying rationale of Rule 10b-21 Hypothesis

Parsons and Raviv (1985) developed a theoretical model to explain the underpricing of SEOs. The model assumes two types of investor according to expectation of the share value in the market. The underwriter sets an optimal market price, and then the two types of investor react to this choice according to their own circumstances. The study points out that the underpricing is the result of the potential for oversubscription and the rationing that will follow. The study emphasises that restriction against short selling is a critical assumption in the model, illustrating that short-sale restrictions make existing share prices less informative and cause the underwriters to give larger discounts to counteract the uncertainty.

Following this idea, Kim and Shin (2004) suggested that traders took short position before the SEO and drove down the market price and after the offering the same traders used the shares acquired from the offering to cover the short positions. When Rule 10b-21 was implemented, the above trading strategy became restricted. Rule 10b-21 was intended to minimise manipulative short selling prior to SEOs. Thus the expected effects would be less negative abnormal return of the underlining shares prior to the offerings if the rule was successful.

However, Corwin (2003) and Kim and Shin (2004) found that abnormal negative returns even increased after the implementation of Rule 10b-21, indicating the failure of the intention of Rule 10b-21. Indeed, Rule 10b-21 restricted informational short sales and reduced the informativeness of prices, thereby increasing required underpricing. Empirical results from both Kim and Shin (2004) and Corwin (2003) prove that the implementation of Rule 10b-21 had positive effects on SEO

underpricing. Kim and Shin (2004) exhausted all the possible explanations they could find and argue that none can explain the puzzling increase of SEO underpricing. As a result, they attribute the implementation of Rule 10-b21 as the reason for the increase of SEO underpricing.

5.1.2. Evidence Inconsistent with the Hypothesis of Rule 10b-21 Implementation

As pointed out by Corwin (2003), the increase of underpricing was gradual over time in his sample, and the variation through time cannot be captured by a simple shift in the regression intercept following the implementation of Rule 10b-21. To illustrate the behaviour of SEO underpricing over time, we adopt the estimation method in Chambers and Dimson (2009).

First, the following empirical model of SEO underpricing is employed.

$$\begin{aligned} \text{Underpricing} = & b_0 + b_1 \text{MarketCap} + b_2 \text{Volatility} + b_3 \text{Reloffersize} + \\ & b_4 \text{CARPos} + b_5 \text{CARNeg} + b_6 \text{LnPrice} + b_7 \text{Cluster} + b_8 \text{NYSEDummy} + \\ & b_9 \text{IPOUnderpricing} + b_{10} \text{Underwriter} + b_{11} \text{Year} + \varepsilon. \end{aligned} \quad (5.1)$$

The model is based on Corwin (2003). *MarketCap* is defined as the prior closing price multiplied by the shares outstanding on the day prior to the offer. *Reloffersize* is defined as the ratio of the number of shares offered to the total number of outstanding shares prior to the offer. *Volatility* is represented by the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer⁶⁰. *CARPos(Neg)* is defined as the cumulative market-adjusted return over the 5 days

⁶⁰ The definition is the same as that in Corwin (2003).

prior to the offer and it equals zero if the return is positive (negative), where market return is defined as the return on the CRSP value weighted index. *LnPrice* is the logarithm of closing price on the day prior to the offer, and *Cluster* is a dummy variable equal to one if the offer price is set at integer and equal to zero otherwise.

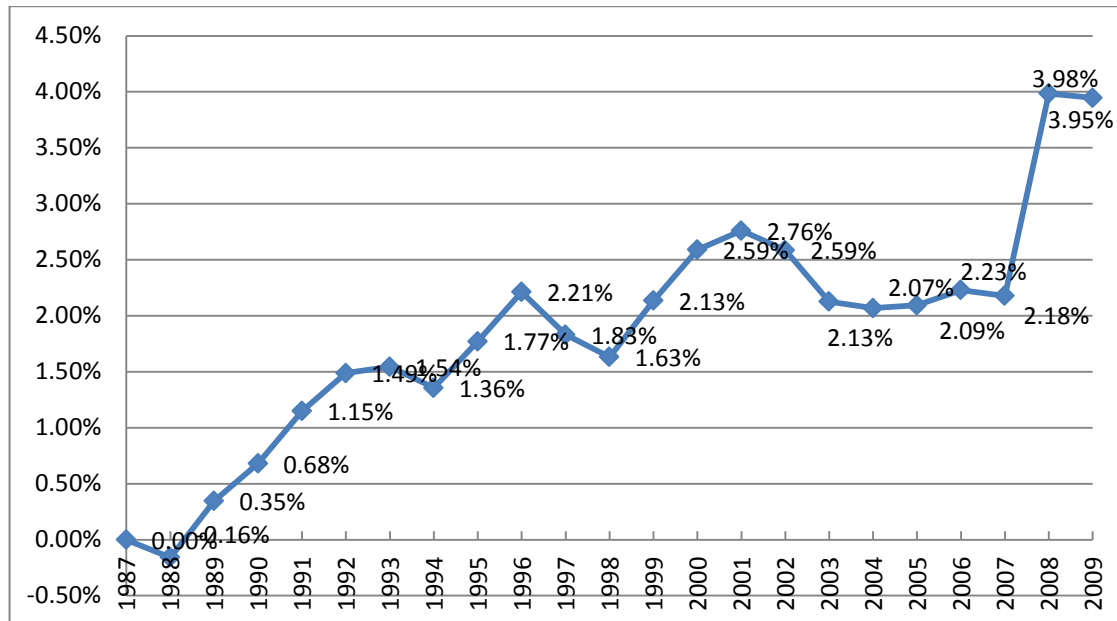


Figure 5-1 Coefficients of the year dummy

NYSEDummy is a dummy variable equal to one if the issuer is listed on NYSE and equal to zero otherwise. *IPOUnderpricing* is the average monthly IPO underpricing available from Ritter's website. *Underwriter* is a dummy which equals one if one of the lead underwriters has the reputation rank equal to or greater than 8 and zero otherwise. *Year* is the dummy variable of the calendar year in which the offer is made. The ranking is made by Ritter, and both the average monthly IPO underpricing and underwriter ranking are available at <http://bear.warrington.ufl.edu/ritter/ipodata.htm>.

The model is estimated with the data in Sample 1. In the sample, we have more than 4500 SEOs from the period 1987 to 2009. Then the estimation method in Chambers and Dimson (2009) is then employed. Specifically, with the exception of year, all other explanatory variables are demeaned in order to assist economic interpretation of the year coefficients. Each year coefficient represents the level of SEO underpricing in a given year by an SEO with characteristics in line with average values for the sample.

Figure 5-1 illustrates the coefficients of the year dummy. The Rule 10b-21 took effects on August 25, 1988, but we find that there seems to be no strong evidence for a jump in SEO underpricing in 1988, after controlling for changing risk composition as well as the influence of underwriter reputation. The coefficient of Year dummy for 1988 was -0.16%, a slight dip from 0 for 1987. According to Figure 5-1, there was an increase in the SEO underpricing from 1988 but the increase was gradual from 1988 to 1996. Therefore, although we cannot rule out the effects of Rule 10b-21, the gradual increase in the SEO underpricing suggests that Rule 10b-21 at least is unlikely to explain the pattern of the SEO underpricing during the 1990s.

5.2. Investment Banking Power Hypothesis

Besides the Rule 10b-21 hypothesis, Mola and Loughran (2004) proposed that the reason for the increase of SEO underpricing is investment banking power, which increased during the 1990s. To support their argument, they point out two pieces of evidence: 1) the rise in integer offer prices set at least one dollar below the prior close price; 2) offerings underwritten by banks with top tier analysts show greater SEO underpricing than others.

5.2.1. Setting Offer Price at Integer

As discussed in Chapter Four, it is highly likely that Mola and Loughran (2004) did not adjust the offer day provided by the SDC database. Therefore, it is worth checking their findings with the adjusted database in this section. In the previous chapter, the pattern of SEO underpricing was discussed. This section checks 1) the distribution of closing prices on the day before the SEO and 2) whether there is a rise in integer offer prices set at least one dollar below the prior close price.

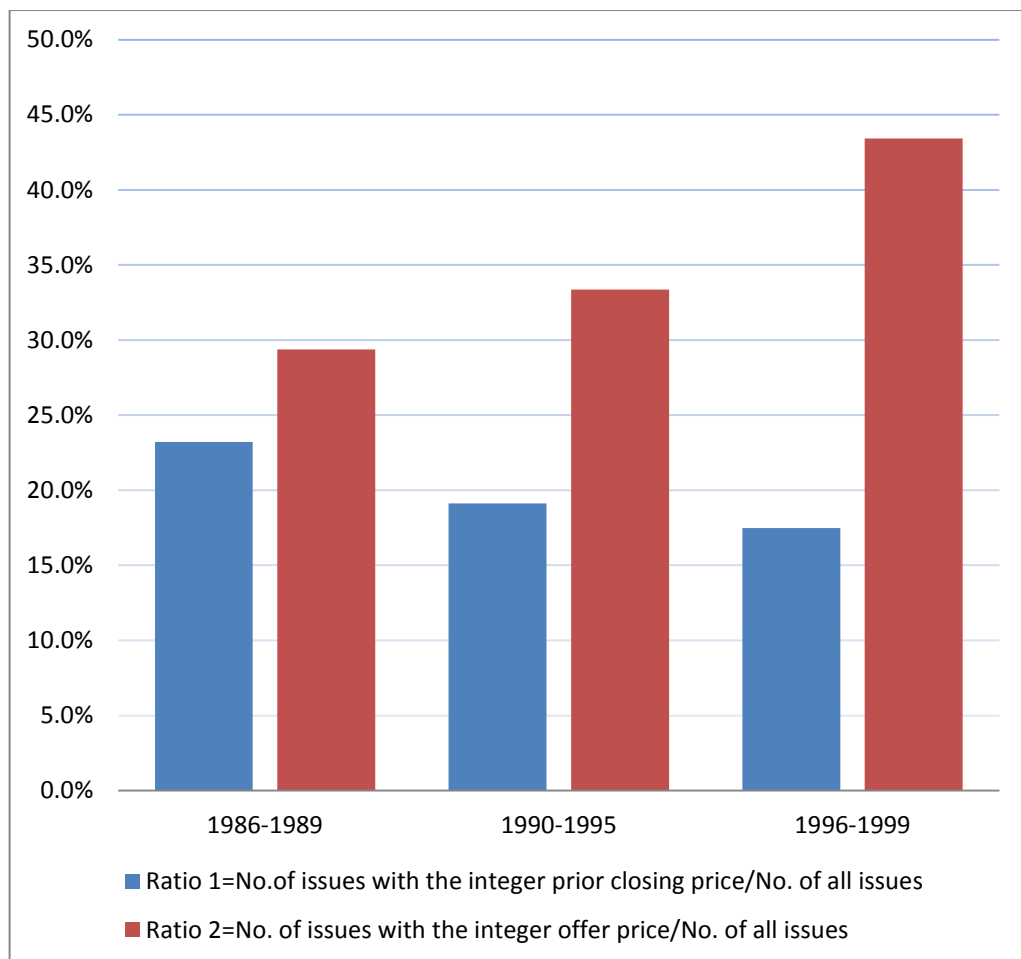


Figure 5-2 Trend of clustering in integer offer price

On April 9, 2001, the US Securities and Exchange Commission ordered all US stock markets to convert to decimals. Before that date the shares were priced by dollar fractions. There were five classes of dollar fractions, namely zero, even-eighths, odd-eighths, odd-sixteenths and other. After adjusting the offer dates, Figure 5-2 shows two opposite trends. One trend is the decrease in the ratio of issues with the integer prior closing price to all issues in each sub period. The ratio in 1986-1989 was 23.22%, but it declined to 17.47% in 1996-1999. The other trend is that the ratio of issues with an integer offer price to all issues rose. The ratio in 1986-1989 was 29.38% and it rose substantially to 43.43% in 1996-1999.

Based on this sharp comparison, it might be concluded that there is a trend for investment banks to set offer prices at integer deliberately rather than just set the offer price at the prior closing price. This result is consistent with Mola and Loughran (2004), suggesting the trend still holds after adjusting offer dates. Among those issues with an integer offer price, there is also a trend that more offer prices are set at the next lower integer or other lower integers. This trend is confirmed by Figure 5-3. These results obtained with the adjusted database are similar to the results reported by Mola and Loughran (2004).

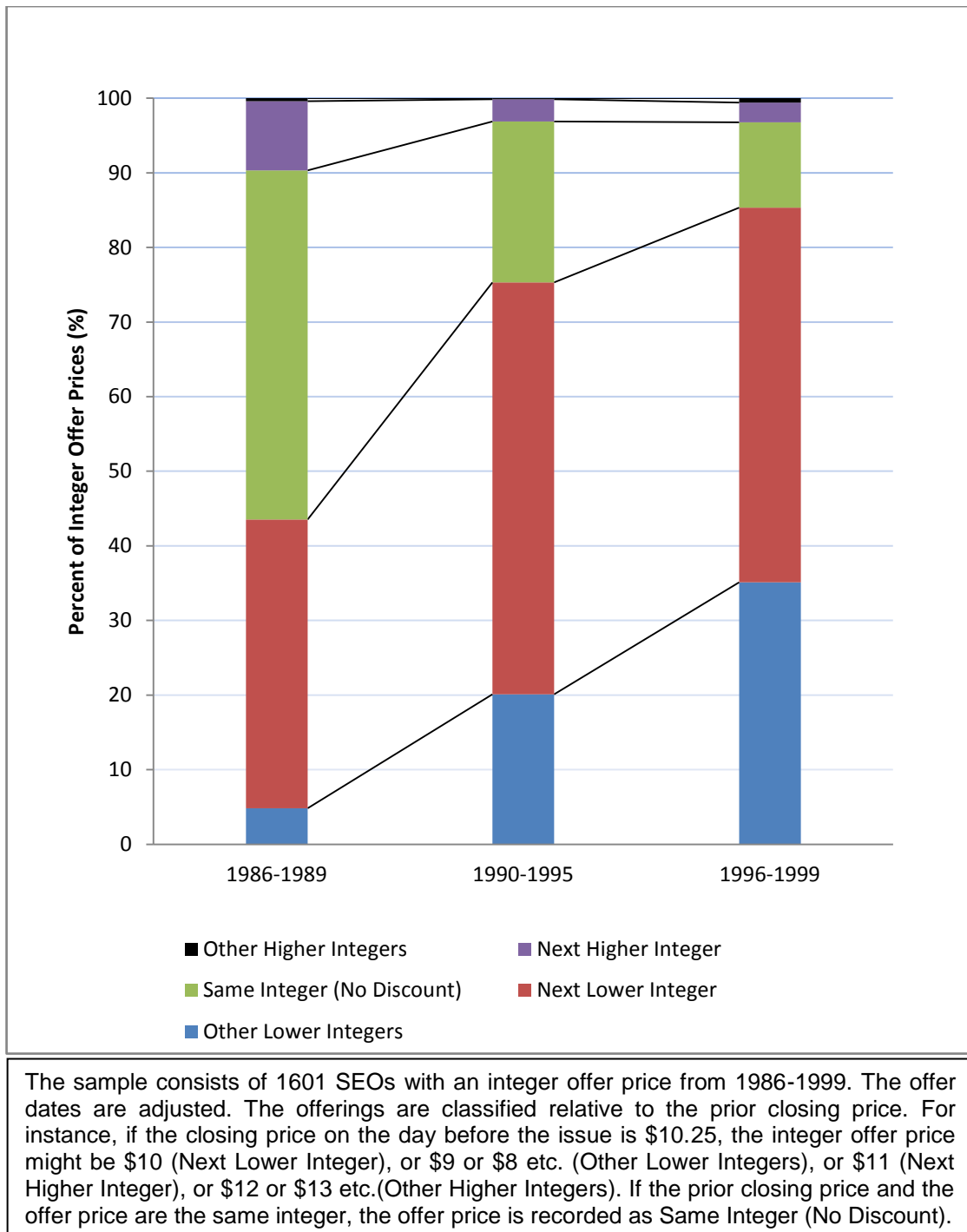


Figure 5-3 Integer offer price clustering relative to the prior closing price categorised by subperiods (with offer dates adjusted)

5.2.2. Analyst Coverage and SEO Underpricing

“What allows underwriters to round down offer prices more often in the 1990s than in the 1980s? Alternatively, why do issuers allow bankers to price offerings down, and thus leave more money on the table for investors?” (Mola and Loughran, 2004, p14). Mola and Loughran (2004) hypothesise that issuers are willing to accept more SEO discount or underpricing because they place more importance on analyst coverage. Thus investment banks use analyst coverage to assist in extracting rents from issuers via clustering of offer price. In other words, issuers purchase analyst coverage with SEO underpricing. Mola and Loughran (2004) call this hypothesis the investment banking power hypothesis.

The investment banking power hypothesis in Mola and Loughran (2004) is not new in the literature of equity underpricing. For IPO underpricing, the analyst coverage is often considered as a determinant. For instance, Loughran and Ritter (2004) hypothesise that there was an increased emphasis on analyst coverage during their sample period. As issuers placed more weight on hiring a lead underwriter with a highly reputable analyst team to cover the firm, they became less concerned about avoiding underwriters with a reputation for excessive underpricing. Cliff and Denis (2004) also report that IPO underpricing is positively related to analyst coverage by the lead underwriter and to the presence of an all-star analyst on the research staff of the lead underwriter. Moreover, Liu and Ritter (2011) included all-star analyst coverage in their models and found that all-star analyst coverage is positively and significantly related to IPO underpricing.

To capture the quality of analyst groups, Mola and Loughran (2004) used a dummy variable $TOP-TIER ANALYST_{j, T-1}$ which equals one when the underwriter has an analyst group among the top 10 bankers selected by *Institutional Investor* in October of each year⁶¹. The definition of analyst coverage is similar to that in Cliff and Denis (2004)⁶² and Liu and Ritter (2011)⁶³. Mola and Loughran (2004) expected this dummy variable to have a significantly negative relation with SEO discount (SDC).

However, as mentioned previously, this conclusion is highly likely to have been drawn based on the sample without offer date correction. This study presents the comparison of two sets of regression results in Table 5-1. Model 3 is the original regression results presented by Mola and Loughran (2004)⁶⁴. Model 1 is our replication of Mola and Loughran's model without offer date adjustment.

According to Table 5-1, the results of Model 1 and Model 3 are qualitatively the same. Specifically, in both patterns, the coefficients of $TOP-TIER ANALYST_{T-1}$ are positively related to SEO underpricing and statistically significant level at conventional levels. The coefficient means in Model 1 show that if the issue is underwritten by an investment bank with a top-tier analyst team, the issuer has to give around 40 basis points to the SEO underpricing. This result is almost the same as the 47 basis points suggested by the original regression results. Besides that, almost all other variables in

⁶¹ In their study, the underwriter means book manager in SDC database.

⁶² Cliff and Denis (2004) match an IPO to an all-star if the lead underwriter has an all-star (first-, second-, or third-team) in the same industry as the issuer in the year of the issue or the prior year.

⁶³ Liu and Ritter (2011) define the all-star analyst coverage variable as a dummy that equals one if an all-star analyst (top three) from a lead underwriter has covered the stock within a year after its IPO, and zero otherwise. For IPOs in year t , they use the October Issue of *II* for year $t-1$ to classify IPOs as to whether coverage from a lead underwriter was provided by an all-star analyst.

⁶⁴ The full regression results of Mola and Loughran (2004) can be found in Table 6, p18, VOL 39, NO. 1, March 2004, *Journal of Financial and Quantitative Analysis*.

Model 1 and Model 3 have the same sign and similar scale. These results suggest that the regression test in Mola and Loughran (2004) is highly likely done without offer date adjustment.

Table 5-1 Mola and Loughran's OLS models of SEO discount (SDC)

	Model 1	Model 2	Model 3
NASDAQ Dummy	0.0060*** (3.71)	0.0054*** (3.85)	0.0062*** (4.04)
PROCEEDS/MKT	0.0086 (1.61)	0.0086* (1.87)	0.0095 (1.37)
UTILITY Dummy	-0.0072*** (-2.65)	-0.0076*** (-3.27)	-0.0041* (-1.72)
TECH Dummy	0.0059*** (3.38)	0.0031** (2.10)	0.0069*** (3.32)
LNPRICE	-0.0120*** (-7.73)	-0.0122*** (-9.13)	-0.0105*** (-5.04)
GROSS SPREAD	0.0029*** (3.77)	0.0028*** (4.26)	0.0058*** (5.34)
PRIOR SEO Dummy	-0.0018 (-0.81)	-0.0011 (-0.55)	-0.0029 (-1.63)
UNDERWRITER REPUTATION Dummy	-0.0066*** (-3.41)	-0.0066*** (-3.99)	-0.0052** (-2.40)
TOPTIER ANALYST _{T-1}	0.0040** (2.47)	0.0006 (0.40)	0.0047*** (2.74)
CLUSTER Dummy	0.0142*** (9.99)	0.0105*** (8.66)	0.0150*** (9.36)
Constant	0.0416*** (5.33)	0.0423*** (6.31)	0.0224** (2.17)
No. of Obs.	4342	4347	4417
Adjusted R ²	0.1062	0.1320	0.11

Model 1 is the replication of Mola and Loughran (2004). Model 3 is the original results of Mola and Loughran (2004). Model 2 is the replication of the model based on the corrected offer date. All variables are exactly the same as in Mola and Loughran (2004). The dependent variable, SEO underpricing, is computed as $[(P_{T-1} - OP)/OP]$ OP is the offer price and P_{T-1} is the prior closing price. NASDAQ is a dummy variable equal to one if the issuing firm is listed on Nasdaq, and zero otherwise. PROCEEDS/MKT is a ratio of issue proceeds and issuer market value. UTILITY and TECH are dummies equal to one if the issuer operates, respectively, in the two-digit SIC industry of 49 and in SIC codes specified in Loughran and Ritter (2002). LNPRICE is the natural logarithm of the closing price of the day before the issue in dollars. GROSS SPREAD is the total fee of underwriters, expressed as a percentage of the issue proceeds. PRIOR SEO is a dummy equal to one if the firm issued seasoned equity in the prior year. UNDERWRITER REPUTATION is a dummy equal to one if the lead manager has a reputation rank equal to or greater than eight, as determined in Loughran and Ritter (2002) and zero otherwise. TOP-TIER ANALYST_{T-1} is a dummy equal to one if the SEO underwriter (book managers) has an analyst group ranked among the top 10 groups selected by institutional investor each October of the prior calendar year and zero otherwise. CLUSTER is a dummy variable equal to one if the offer price is set at integers or zero if the offer price is set in dollar fractions. PROCEEDS/MKT and LNPRICE are winsorized at the 1% and 99% levels. White's heteroskedasticity-adjusted t-statistics are in parentheses. ***, **, and* represent 1% 5% and 10% significance, respectively.

After adjusting the offer dates, the main difference between Model 2 and Model 1 is the coefficient of *TOP-TIER ANALYST_{T-1}*. Although the sign of the coefficient remains positive, it is no longer significant. After the adjustment of offer dates, issues underwritten by investment banks with high reputations are priced at fewer discounts than others while controlling for other factors. *CLUSTER Dummy* and *LNPRICE* are also important factors. The significantly negative coefficient of *LNPRICE* suggests that issues with high price in the secondary market often have less underpricing after controlling other factors. This result partially proves that offer price rounding is positively related to SEO underpricing.

Moreover, in the original results, rounding offer price adds 142 basis points to the SEO underpricing after controlling for other factors. After the adjustment, rounding offer price adds 105 basis points. This comparison suggests that pricing at integers is an important factor in determining SEO underpricing even after the adjustment. Indeed, the variable *CLUSTER Dummy* is the most economically and statistically significant variable in the regression. In Table 5-2, the regression results of the three sub-periods are reported using the sample with offer dates adjusted⁶⁵. Three sub-periods are the same as in Mola and Loughran (2004). The coefficient of *CLUSTER Dummy* is statistically insignificant in the first period. This result suggests that the practice of setting offer prices at integers was becoming popular in the 1990s. None of the coefficients of *TOP-TIER ANALYST_{T-1}* during the three sub-periods are statistically significant.

⁶⁵ The original results reported by Mola and Loughran (2004) can be found in Table 7, p20, VOL 39, NO. 1, March 2004, Journal of Financial and Quantitative Analysis.

Table 5-2 Mola and Loughran's OLS models of SEO discount (SDC) over three subperiods

	1986-1989	1990-1995	1996-1999
NASDAQ Dummy	-0.0040 (-1.20)	0.0071*** (3.94)	0.0048* (1.89)
PROCEEDS/MKT	0.0004 (0.03)	0.0001 (0.01)	0.0112 (1.47)
UTILITY Dummy	-0.0045 (-0.89)	-0.0087*** (-3.09)	-0.0064 (-1.20)
TECH Dummy	-0.0079* (-1.86)	0.0014 (0.74)	0.0065*** (2.68)
LNPRICE	0.0014 (0.36)	-0.0166*** (-9.38)	-0.0194*** (-8.39)
GROSS SPREAD	0.0040** (2.51)	0.0022*** (2.68)	0.0071*** (5.13)
PRIOR SEO Dummy	-0.0021 (-0.36)	-0.0017 (-0.69)	0.0004 (0.14)
UNDERWRITER REPUTATION Dummy	-0.0031 (-0.70)	-0.0097*** (-4.58)	0.0012 (0.42)
TOPTIER ANALYSTT-1	-0.0012 (-0.37)	0.0018 (0.99)	0.0025 (1.03)
CLUSTER Dummy	0.0010 (0.31)	0.0077*** (4.82)	0.0148*** (7.18)
Constant	-0.0067 (-0.36)	0.0628*** (7.34)	0.0401*** (3.21)
No. of Obs.	837	1999	1511
Adjusted R2	0.0183	0.1979	0.2032
<p>The dependent variable, SEO underpricing, is computed as $[(P_{T-1}-OP)/OP]$ OP is the offer price and P_{T-1} is the prior closing price. NASDAQ is a dummy variable equal to one if the issuing firm is listed on Nasdaq, or zero if the issuing firm is listed on NYSE or Amex. PROCEEDS/MKT is a ratio of issue proceeds and issuer market value. UTILITY and TECH are dummies equal to one if the issuer operates, respectively, in the two-digit SIC industry of 49 and in SIC codes specified in Loughran and Ritter (2004). LNPRICE is the natural logarithm of the closing price of the day before the issue in dollars. GROSS SPREAD is the total fee of underwriters, expressed as a percentage of the issue proceeds. PRIOR SEO is a dummy equal to one if the firm issued seasoned equity in the prior year. UNDERWRITER REPUTATION is a dummy equal to one if the lead manager has a reputation rank equal to or greater than eight, as determined in Loughran and Ritter (2002). TOP-TIER ANALYST_{T-1} is a dummy equal to one if the SEO underwriter (book managers) has an analyst group ranked among the top 10 groups selected by institutional investor each October of the prior calendar year. CLUSTER is a dummy variable equal to one if the offer price is set at integers or zero if the offer price is set in dollar fractions. PROCEEDS/MKT and LNPRICE are winsorized at the 1% and 99% levels. White's heteroskedasticity-adjusted t-statistics are in parentheses.</p>			

The insignificant coefficients of *TOP-TIER ANALYST_{T-1}* suggest that banks with a prestigious analyst team do not press issuers to give more issue discounts (SDC). As analyst coverage is only one proxy of investment banking power, the insignificant coefficients of analyst coverage cannot rule out the possibility that investment banking power can be captured by other proxies. Therefore we cannot rule out the hypothesis that investment banking power is the reason for the increase of SEO underpricing or discount. Our findings suggest that for SEOs, there is no solid evidence supporting that analyst coverage is significantly and positively related to SEO underpricing.

5.3. Changing Issuer Composition Hypothesis

Issuer characteristics have an important role in deciding the underpricing of SEOs. This argument is already supported by many empirical studies (e.g. Chemmanur et al., 2009; Autore, 2011; Huang and Zhang, 2011). In Table 5-1, the regression results also show that NASDAQ issues have higher SEO underpricing than exchange issues after controlling other factors. SEOs issued by utility firms have lower underpricing than others due to the low risk for utility firms. Therefore, the changing issuer composition hypothesis proposed by Loughran and Ritter (2004) and Mola and Loughran (2004) is a possible explanation for the increase of SEO underpricing.

This hypothesis was checked by Mola and Loughran (2004), who concluded that the changing issuer composition hypothesis can partially explain the increase of SEO underpricing. However, as mentioned earlier, the conclusion was highly likely based on an unadjusted database. In this section, we re-examine the hypothesis with the adjusted database.

Mola and Loughran (2004) categorised issues by the exchange, relative issue size, utility and high tech industry⁶⁶. In this section, the fifth proxy for uncertainty-volatility is added⁶⁷. The first proxy for uncertainty is the primary exchange where the shares of the issuing firm are traded. As discussed in previous chapters, NASDAQ firms are generally different from firms listed on the NYSE or Amex in terms of age, capitalisation, and risk level. The second proxy is the relative size of SEOs. This variable is calculated by the proceeds divided by the market value of outstanding shares prior to the offering.

Higher relative size means more price pressure and greater uncertainty associated with the issue (Scholes, 1972). Mola and Loughran (2004) define this proxy as high when the relative size is equal to or greater than the median of the sample distribution. The third and fourth proxies are utilities and tech industries. If the firm is regarded as utility (tech) firm, it is often regarded as less (more) risky than others. Last but not least, volatility is calculated as the standard deviation of daily close-to-close returns over 30 trading days ending 11 days prior to the offer⁶⁸. This number is regarded as high if the volatility equals or exceeds the median of the sample distribution.

According to the results in Table 5-3, although the percentage of issues associated with high uncertainty is increasing (for instance, the percentage of NASDAQ issues to all issues increases from 55.09% in period 1 to 67.47% in period 3), SEO underpricing has generally increased for both riskier and less risky issues. For example, high

⁶⁶ High tech firms are defined as firms with SIC codes as follows: 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7378 and 7379.

⁶⁷ The volatility commonly used in literature is not included by Mola and Loughran (2003).

⁶⁸ This definition is used by Corwin (2003)

volatility issues report an average underpricing increasing from 1.45% in period 1 to 3.69% in period 3, while the average underpricing for low volatility issues increases from 0.93% to 1.95%. Although the increase is more substantial for riskier issues, the p-value for diff (d)-(b) suggests that all issues experienced a statistically significant increase in SEO underpricing except for utility issues. These results are consistent with similar tests made by Mola and Loughran (2004). Therefore, it is safe to conclude that after the adjustment of offer date, the changing composition hypothesis still cannot completely explain why the SEO underpricing has increased.

5.4. Leaving a Good Taste Hypothesis

The leaving a good taste hypothesis was proposed by Jegadeesh et al. (1993). The hypothesis was inspired by several theoretical models such as Allen and Faulhaber (1989), Welch (1989), and Chemmanur (1993). These models assume that the issuers possess superior information and take into account the possibility of future equity offerings in deciding IPO prices. High quality firms deliberately underprice their IPOs more substantially than low quality firms in order to raise more funds. After checking a sample of 1985 IPOs from 1980 to 1986, Jegadeesh et al. (1993) found a positive relationship between IPO underpricing and the probability and size of subsequent seasoned offerings. However, the economic significance was weak in their test. Spiess and Pettway (1997) found no evidence that firms cover the cost of an underpriced IPO in either higher issue proceeds or in greater wealth for the firm's initial owners.

For SEOs, the leaving a good taste hypothesis is already examined in Table 5-1 and Table 5-2. The variable PRIOR SEO Dummy is equal to one if the firm issued an SEO

in the prior year, and zero otherwise. If the hypothesis holds for SEO underpricing, we expect a significant positive relationship between PRIOR SEO Dummy and SEO underpricing. However, the insignificant coefficients in Table 5-1 and Table 5-2 suggest that there is little support for the leaving a good taste hypothesis in our sample.

Table 5-3 Average SEO discount (SDC) categorised by proxies of uncertainty

	Overall			1986-1989			1990-1995			1996-1999					
Proxies	Discount (a)	N	Percent	Discount (b)	N	Percent	Discount (c)	N	Percent	Discount (d)	N	Percent	p-value for Diff (c)-(b)	p-value for Diff (d)-(c)	p-value for Diff (d)-(b)
Primary Exchange															
NASDAQ Issues	2.98%	2,710	61.23%	1.19%	465	55.09%	3.18%	1,187	58.94%	3.53%	1,058	67.47%	0.0000	0.0264	0.0000
NYSE/Amex Issues	1.45%	1,716	38.77%	1.03%	379	44.91%	1.43%	827	41.06%	1.82%	510	32.53%	0.0364	0.0195	0.0006
Relative size															
High (PROCEEDS/MKT)	3.02%	2,214	50.02%	1.44%	387	45.85%	3.11%	1,030	51.14%	3.67%	797	50.83%	0.0000	0.0037	0.0000
Low (PROCEEDS/MKT)	1.75%	2,212	49.98%	0.85%	457	54.15%	1.78%	984	48.86%	2.26%	771	49.17%	0.0000	0.0023	0.0000
Utility Industry															
Utility Issues	0.71%	334	7.55%	0.39%	85	10.07%	0.78%	183	9.09%	0.93%	66	4.21%	0.0958	0.3377	0.6473
Non-Utility Issues	2.52%	4,092	92.45%	1.20%	759	89.93%	2.63%	1,831	90.91%	3.06%	1,502	95.79%	0.0000	0.0012	0.0000
Tech Industry															
Tech Issues	2.80%	941	21.26%	0.53%	122	14.45%	2.74%	396	19.66%	3.51%	423	26.98%	0.0000	0.0078	0.0000
Non-Tech Issues	2.27%	3,485	78.74%	1.22%	722	85.55%	2.39%	1,618	80.34%	2.77%	1,145	73.02%	0.0078	0.0053	0.0000
Volatility															
High (Volatility) Issues	3.30%	2,218	50.11%	1.45%	309	36.61%	3.51%	988	49.06%	3.69%	921	58.74%	0.0000	0.1913	0.0000
Low (Volatility) Issues	1.47%	2,208	49.89%	0.93%	535	63.39%	1.45%	1,026	50.94%	1.95%	647	41.26%	0.0015	0.0003	0.0000

The sample is obtained from the sampling procedures 2 in Chapter Four. Discount (SDC) is defined as $[(PT-1-OP)/OP]$ OP is the offer price and PT-1 is the prior closing price. The sample consists of 4426 SEOs during the 1986-1999 time period with the offer dates adjusted. Proceeds/MKT is the ratio of the domestic proceeds to the market value. Market value is defined as the number of shares greater than the median value of the distribution. Utility issues are offerings whose firm has a two-digit SIC industry code of 49. Tech issues are defined by using the SIC codes in Loughran and Ritter (2004). Volatility is calculated as the standard deviation of daily close-to-close returns over 30 trading days ending 11 days prior to the offer. Volatility is high when the number is equal to or greater than the median value of the distribution

CHAPTER 6: LIQUIDITY SHOCKS AND SEO UNDERPRICING OVER THE LONG RUN

In this chapter we hypothesise that liquidity shocks caused by certain market conditions can affect the demand for SEO stocks and therefore increase SEO underpricing⁶⁹. We test the hypothesis with our sample and find that market volatility is significantly and positively related to SEO underpricing after controlling for other factors. We then examine the behaviour of SEO underpricing over the sample period from 1987 to 2009 using an estimation method proposed by Chambers and Dimson (2009).

6.1. Hypothesis of Liquidity Shocks caused by Certain Market Conditions

The hypothesis of liquidity shocks is not new for studies of SEO underpricing. In a typical SEO underwriting contract, a syndicate of investment banks guarantees to buy an issuer's entire equity offering at a fixed price. This means that once the contract is signed the banks have to bear the entire price risk associated with reselling the shares to the public. Corwin (2003) suggests that a seasoned offer could be viewed as both permanent price pressure and temporary liquidity shocks that must be absorbed by the market. He also argues that permanent price effects should occur on the announcement day rather than the issue day due to market efficiency. Thus, it is reasonable to refer to the seasoned offer as temporary liquidity shocks that must be absorbed by investors. This idea is consistent with Scholes (1972) and Mikkelson and Partch (1985).

⁶⁹ Unless otherwise stated, underpricing refers to the close-to-offer return in this chapter.

As mentioned in Chapter Three, there are various concepts of liquidity shocks in the literature. For instance, research on mutual funds or hedge funds often interpret cash withdrawn or fund inflows as liquidity shocks (e.g. Ding et al., 2009). Some studies on stock market liquidity assume that liquidity shocks are caused by selling a large amount of asset immediately (e.g. Da and Gao, 2010; Coval and Stafford, 2007). Under this rationale, liquidity shocks can be regarded as the temporary imbalance between supply and demand of the underlying securities. Indeed, the above definition that interprets liquidity shocks as an imbalance between supply and demand is consistent with Corwin (2003), and we therefore adopt that definition in this study.

For temporary liquidity shocks, Corwin (2003) uses relative offer size, which is the ratio of new issues to shares outstanding prior to the issue, as the proxy and reports positive effects on the underpricing at a statistically significant level. Besides Corwin's study, Altinkilic and Hansen (2003), Mola and Loughran (2004), Chemmanur et al. (2009) and Huang and Zhang (2011) use relative offer size as a control variable in their models and report mixed results.

In this study, the hypothesis of liquidity shocks is extended by considering market conditions. We hypothesise that aggregate issues with large proceeds, large market declines and market volatility could cause liquidity shocks that will consequently increase SEO underpricing.

6.1.1. Discussions of Three Scenarios of Market Conditions

We propose three scenarios of market conditions, namely aggregate issues with large proceeds, large market declines and market volatility. Regarding aggregate issues with large proceeds, we assume that aggregate issues with large proceeds during a certain period could draw excessive funding in the market, causing a shortage of funding in the SEO market. Specifically, if issues are regarded as temporary liquidity shocks that must be absorbed by the market, there is a chance that investors will face a funding constraint after engaging in previous offerings with large proceeds during a short period. As a result, the underwriters have to set more issue discounts to attract investors.

Liquidity shocks could also be caused by large market declines and market volatility. Recently, several theoretical studies have tried to explain why market declines cause asset illiquidity. Different theoretical models tell the story of illiquidity after market declines in a variety of ways. There are three main types of model in the literature: collateral-based models (Brunnermeier and Pedersen, 2009; Garleanu and Pedersen, 2007), limits-to-arbitrage models (Kyle and Xiong, 2001; Xiong, 2001), and coordination failure models (Bernardo and Welch, 2004; Stephen Morris and Shin, 2004).

Hameed, Kang and Viswanathan (2010) conducted empirical tests and document economically significant returns to supplying liquidity after large market declines. The SEO market is slightly different from the secondary market in terms of market participants. However, since investors in both markets provide liquidity to the sellers

(issuers), we follow the notion of Hameed, Kang and Viswanathan (2010) that assumes liquidity shocks can be caused by large market declines and market volatility.

Specifically, Garleanu and Pedersen (2007) proposed a theoretical model to explain the relationship between market liquidity and risk management by institutions. According to their model, in market downturns and market volatility, tighter risk management restricts the security position of institutions. If every institution uses a tight risk management strategy, then market liquidity is lowered. Moreover, tighter market liquidity further tightens risk management, causing a spiral.

In the SEO market, there are two types of investors: retail investors and institutional investors, and the importance of institutional investors in equity offerings has increased dramatically in recent years (Chemmanur et al., 2009). Thus, it can be expected that risk management by institutional investors accompanied by large market declines and market volatility reduces the liquidity for the market of seasoned equity offerings. The underwriters therefore have to give more discounts during market declines.

6.1.2. Proxies of Liquidity Shocks caused by Certain Market Conditions

For liquidity shocks caused by aggregate issues with large proceeds, we use the ratio of aggregate SEO proceeds over the 90 trading days ending 1 day before the offer to the overall market capitalisation prior to the offer day.

$$RAProcess90SEO = \frac{\sum_{t-91}^{90} SEO\ Proceeds}{Overall\ Market\ Capitalization_{t-1}}$$

where t is the offer date and overall market capitalisation is the overall capitalisation in CRSP Stock Market Indexes (NYSE/AMEX/NASDAQ/ARCA). SEO proceeds is calculated as the product of number of shares offered and the offer price.

Liquidity shocks caused by market declines are measured by the interaction of market return R_{market} and dummy variable of market downturn D_{market} .

$$Market250 = Return_{market} * D_{market}$$

R_{market} is the accumulated return over the 250 trading days ending 1 day before the offer. D_{market} is a dummy that equals 1 if R_{market} is negative and zero otherwise. The proxy of liquidity shocks caused by market declines is similar to that in Hameed, Kang and Viswannathan (2010). Hameed, Kang and Viswannathan (2010) use 5 trading days to define market decline since their research focuses on trading in the secondary market, but SEOs occur in the primary market and the average transaction size is far more than that in the secondary market. Moreover, in the primary market, given the fact that institutions are often long-term investors, market conditions in the long run should be taken into account instead of in the short run.

Liquidity shocks caused by market volatility are measured by the standard deviations of daily returns, computed using equal-weighted portfolios of all firms listed on NYSE/AMEX/NASDAQ/ARCA for the 21-trading-day returns ending at day $t-1$,

where t is the offer day. The definition is similar to the time-series return volatility measure in Lowry et al. (2010).

6.2. Model Specification and Control Variables

In the literature of SEO underpricing, several studies have already proposed possible explanations for SEO underpricing. In this section, we summarise those explanations that have already been proven to have statistically significant effects on SEO underpricing and incorporate them into the multivariate analysis.

6.2.1. Uncertainty and Asymmetric Information

Several existing studies document that both ex ante price uncertainty and information asymmetry have positive effects on SEO discounts. This is because investors require more compensation when it is difficult to value the firm (Rock, 1986). In this study, two proxies are employed to capture the uncertainty and asymmetric information. One is volatility, defined as the standard deviation of daily stock returns over the 30 trading days 11 days prior to the issue⁷⁰. Volatility directly represents price uncertainty and is associated with levels of asymmetric information. The other proxy is market capitalisation of the underlying issuing firm. Large firms often suffer less information asymmetry than small firms. Therefore market capitalisation is employed as a control variable by a number of studies (e.g. Autore, 2011; Huang and Zhang, 2011).

⁷⁰ This definition of volatility is the same as that in Corwin (2003).

Corwin (2003) suggests that, even in the absence of information asymmetry, the time lag between offer pricing and distribution may still cause a significant relationship between uncertainty and underpricing. For instance, if the offer price is set after the close on day t and the shares are distributed on day $t+1$, there is still a good chance that the share price may drop significantly prior to completion of the offering. In order to make the offering attractive, the underwriter may tend to set the offer price below the most recent market price. The existing literature has shown a positive relationship between volatility and SEO underpricing (e.g. Corwin, 2003; Autore, 2011; Huang and Zhang, 2011).

6.2.2. Manipulative Trading: Preoffer Price Moves

Besides the effects of Rule 10b-21⁷¹, manipulative trading can still reduce the informativeness of the secondary market. Gerard and Nanda (1993), Corwin (2003) and Altinkilic and Hansen (2003) mention that preoffer return may reflect manipulative trading by investors who attempt to depress the offer price by selling in the preoffer secondary market. This manipulation reduces the informativeness of secondary market prices and increases SEO underpricing. However, Gerard and Nanda (1993) propose an opposing effect related to preoffer price changes. If underwriters account for these temporary preoffer price changes, temporary price increase (decline) in the days prior to the offer may lead to a larger (smaller) size of SEO underpricing.

⁷¹ The effects of Rule 10b-21 have been thoroughly discussed in Chapter Five.

Moreover, Kim and Park (2005) propose that positive preoffer price moves reduce issuers' willingness to bargain over offer price with underwriters. The empirical results of Corwin (2003), Altinkilic and Hansen (2003) and Kim and Park (2005) show that a positive relationship between preoffer price movement and SEO underpricing. Corwin (2003) and Altinkilic and Hansen (2003) further point out that both higher positive preoffer price moves and negative preoffer price moves are related to higher SEO underpricing.

6.2.3. Underwriter Pricing Practice

In this section, we discuss two types of underwriter pricing practice. One practice is setting offer prices at next lower integer or other lower integers. The other is setting offer price at the closing bid. The first practice has become prevalent since the 1990s, while the latter one was popular during the 1990s and then diminished in the 2000s.

6.2.3.1. Setting Offer Price at Integer

Several studies document the increasing effects of investment banking practice on SEO discounts. Two significant practices have been reported. One is the increasing clustering of setting offer prices at integer values. The other is the practice of setting offer prices at the closing bid price prior to the offer. Mola and Loughran (2004) propose the argument that the tendency for underwriters to set offer prices at an integer more frequently than before is evidence of increased investment banking power. Other studies (e.g. Chemmanur et al., 2009) at least regard cluster of offer price as an underwriting practice.

In our sample, the cluster of integer offering price is again confirmed. Overall, there are 1902 issues with integer offer prices in our sample of 5347 issues, indicating that 35% of all issues had integer offer prices. Figure 6-1 illustrates the trend for clustering in offer price. In 1987-1995, there were 397 issues with integer closing price, representing about 20% of all issues. In the same period, 634 issues or 32% of all issues had an integer offer price. The difference between the two ratios illustrates that underwriters already had the practice of setting offer prices at an integer.

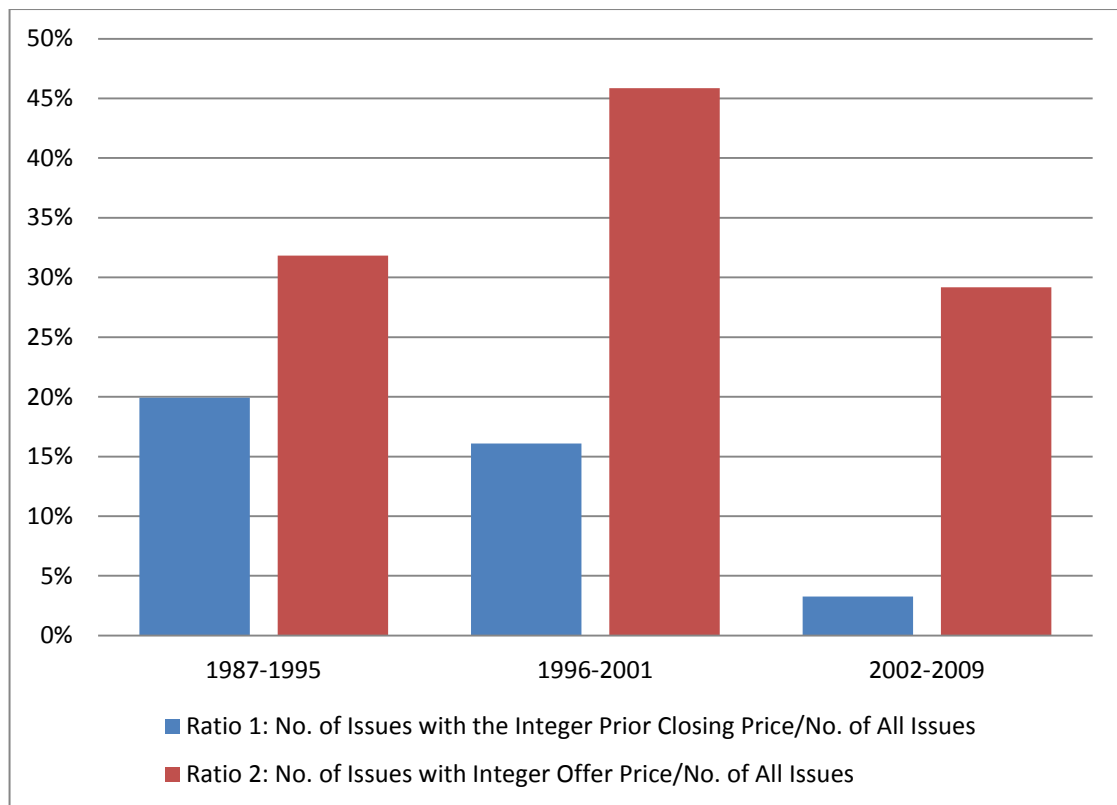
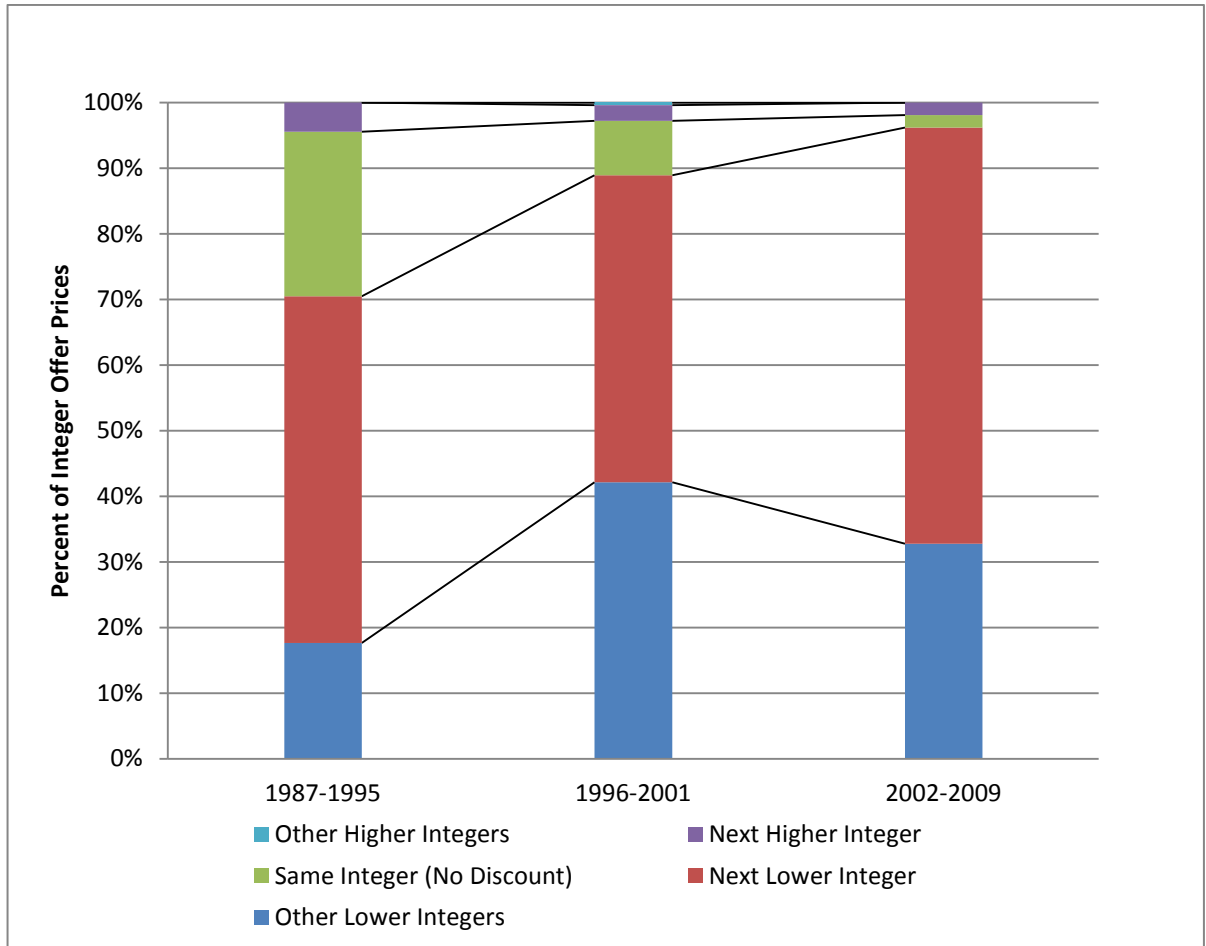


Figure 6-1 Trend of cluster in integer offer prices

This practice is again documented in the second period in our sample. In 1996-2001, although the number of issues with integer closing price declined to 279 (16% of all issues), the number of issues with integer offer price increased to 795 (46% of all issues).

issues). This comparison suggests that the practice of setting offer prices at integer was gaining prominence among underwriters.



The sample consists of 1902 SEOs with an integer offer price from 1987-2009. The offer dates are adjusted. The offerings are classified relative to the prior closing price. For instance, if the closing price on the day before the issue is \$10.25, the integer offer price might be \$10 (Next Lower Integer), or \$9 or \$8 etc. (Other Lower Integers), or \$11 (Next Higher Integer), or \$12 or \$13 etc. (Other Higher Integers). If the prior closing price and the offer price are the same integer, the offer price is recorded as Same Integer (No Discount).

Figure 6-2 Integer offer price clustering relative to the prior closing price categorised by subperiods

In the third period, there was a major change in the external conditions for setting prices at integer. On April 9, 2001, the US Securities and Exchange Commission ordered all US stock markets to convert to decimals. As a result, we can observe a substantial decline of issues with integer closing price. Only 53 issues had integer closing prices among 1621 issues from 2002-2009, representing 3.27% of the sub sample. Still, we can observe that 473 issues in 2002-2009 were priced at integer (29% of the sub sample).

This result suggests that setting integer offer prices is still popular among underwriters. Figure 6-2 provides further evidence for the practice of setting offer prices at integer. In 1987-1995, around 70% of issues with integer offer prices had their prices set at next lower integer or other lower integers. However, this ratio increased to 89% in 1996-2001 and 95% in 2002-2009, representing 707 and 455 issues, respectively.

6.2.3.2. Setting Offer Price at the Closing Bid

As for setting offer prices at the closing bid, this practice, as documented by Lee et al. (1996) and Corwin (2003), was quite common for NASDAQ offers in the 1990s. Particularly, setting offer prices at the closing bid was quite common for NASDAQ offers but not common for NYSE offers during the 1990s. According to Corwin (2003), this NASDAQ-only practice is confirmed by market professionals. The reason why this practice is so largely implemented on the NASDAQ market is the different information reflected by closing prices on the two markets.

Closing price on the NYSE is a centralised closing price and is likely to reflect the aggregate supply and demand of the security because each security is assigned to a

single specialist who handles the majority of order flow, whereas trading on the NASDAQ is dealt with by multiple market makers and closing price is the last reported trade from a single market maker, which does not necessarily reflect information available across all NASDAQ market makers. As a result, the closing bid is perceived as a better indicator of selling price than the closing trade price for NASDAQ securities.

Table 6-1 Pricing at the prior closing price and the prior closing bid

Panel A 1987-2009				
	All Cases		Prior Closing Price!=Prior Closing Bid	
	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid
All Issues	635	1089	295	760
4761	13.34%	22.87%	6.20%	15.96%
NYSE	251	109	208	66
1326	18.93%	8.22%	15.69%	4.98%
NASDAQ	373	980	87	694
3435	10.86%	28.53%	2.53%	20.20%
Panel B 1987-1995				
	All Cases		Prior Closing Price!=Prior Closing Bid	
	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid
All Issues	390	673	170	453
1500	26.00%	44.87%	11.33%	30.20%
NYSE	141	65	107	31
276	51.09%	23.55%	38.77%	11.23%
NASDAQ	249	608	63	422
1224	20.34%	49.67%	5.15%	34.48%
Panel C 1996-2001				
	All Cases		Prior Closing Price!=Prior Closing Bid	
	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid
All Issues	212	405	107	300
1660	12.77%	24.40%	6.45%	18.07%
NYSE	93	37	86	30
393	23.66%	9.41%	21.88%	7.63%
NASDAQ	119	368	21	270
1267	9.39%	29.04%	1.66%	21.31%
Panel D 2002-2009				
	All Cases		Prior Closing Price!=Prior Closing Bid	
	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid	Offer Price=Prior Closing Price	Offer Price= Prior Closing Bid
All Issues	22	11	18	7
1601	1.37%	0.69%	1.12%	0.44%
NYSE	17	7	15	5
657	2.59%	1.07%	2.28%	0.76%
NASDAQ	5	4	3	2
944	0.53%	0.44%	0.44%	0.22%

Corwin (2003) used the percentage difference between the closing transaction price and the closing bid quote (*CloseBidDiff*) to test the practice of pricing at the bid quote. If SEO underpricing is completely explained by that practice, the coefficient of *CloseBidDiff* will be one. Corwin (2003) reports the coefficient of *CloseBidDiff* at about 0.7, which empirically proves the practice of pricing at the bid quote.

Table 6-1 provides an overall picture of setting offer price at the closing bid prior to the offer in our sample. Among 4761 issues, 1089 issues were set with offer price at the closing bid prior to the offer, representing 22.87% of all issues⁷². 635 or 13.34% of all issues had offer prices set at the closing transaction price on the day prior to the offer. For the cases where the prior closing price is not equal to prior closing bid, 760 or 15.96 % of all issues were priced at prior closing transaction price.

Consistent with the literature, this practice is especially popular among NASDAQ issues. 28.53% of all NASDAQ issues were priced at prior closing bid. Even for the cases with the prior closing price different from prior closing bid, 20.20% of all NASDAQ issues were priced at prior closing bid. However, this practice lost its prominence over time. In 1987-1995, 49.67% of all NASDAQ issues were priced at prior closing bid. However, this ratio drops to 29.04% for the period 1996-2001. Moreover, this practice seems to have been completely abandoned by underwriters in the third period. The change can be partially explained by the gradual popularity of integer offer prices. As more and more issues were priced at integer, the practice of

⁷² We exclude issues without bid, ask price at CRSP so that the sample size reduces to 4761.

setting offer prices at prior closing bid was apparently losing its prominence for NASDAQ issues.

6.2.4. Underwriter Quality: Underwriter Rankings and Top-tier Analyst

For studies of IPO underpricing, underwriter quality is widely considered to be important. Carter and Manaster (1990) first proposed the reputation ranking of underwriters. The ranking for the most prestigious underwriters is 9 and least prestigious is 1. This reputation ranking system was extended by Carter, Dark and Singh (1998). Loughran and Ritter (2004) updated the rankings to 2004, loosely based on the previous two rankings.

The ranking updated to 2009 can be downloaded from Jay Ritter's web page at <http://bear.warrington.ufl.edu/ritter/ipodata.htm>⁷³. The hypothesis of underwriter reputation is that more prestigious underwriters can attract more investors and thereby less SEO underpricing is needed. In the literature on SEO underpricing, Mola and Loughran (2004) constructed an underwriter reputation dummy based on the reputation ranking. The dummy equals one if one of the lead underwriters has a reputation rank equal to or greater than 8 and zero otherwise. Their study found a significantly negative relationship between reputation dummy and SEO underpricing.

⁷³ Ritter's ranking is slightly different from Carter and Manaster: most prestigious underwriters are 9.1 and least prestigious are 1.1.

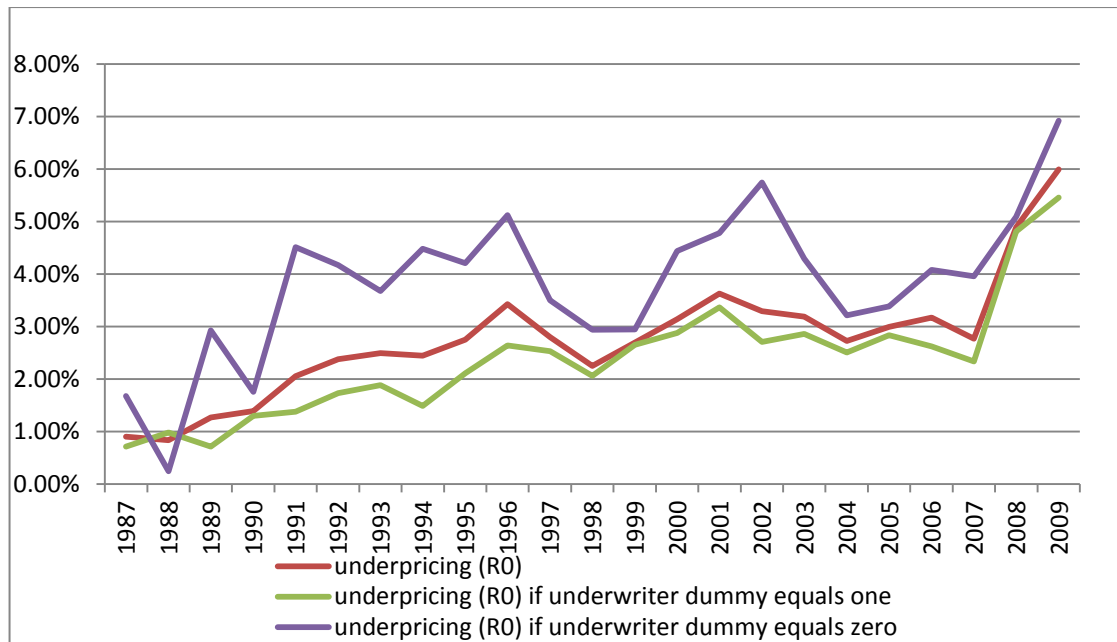


Figure 6-3 SEO underpricing by underwriter category

Similarly, Kim and Shin (2004) used the rankings directly in their regression and found that the reputation rankings are negatively related to SEO underpricing at a statistically significant level after controlling for other factors. Chemmanur, He and Hu (2009) constructed a reputation dummy equal to one if the highest lead underwriters' reputation dummy was 9.1 and zero otherwise⁷⁴. In their regression, the dummy was negatively related to SEO underpricing at a statistically significant level.

In our study, we construct the underwriter reputation dummy using the method used by Mola and Loughran (2004). Figure 6-3 illustrates effects of underwriter reputation on SEO underpricing. Issues underwritten by investment banks with prestigious reputations are substantially less underpriced than others over time. This difference in underpricing suggests that prestigious investment banks may attract more investors and therefore help issuers to reduce the underpricing.

⁷⁴ The reason why 9.1 is used is because Chemmanur et al use Ritter's ranking.

Two studies of SEO underpricing take account of analyst coverage but their conclusions are inconsistent. Mola and Loughran (2004) constructed a dummy variable *Toptier dummy* equal to one if the analyst team of the underwriters was the top ten team ranked by *Institutional Investors* in the prior year. They claim a significantly positive relationship between the dummy and SEO underpricing. This finding is used to support their hypothesis of investment banking power, since they argue that banks with top-tier analysts can press issuers to leave more money on the table. However, as we discussed earlier in Chapter Five, their conclusion was highly likely based on a database without offer date correction.

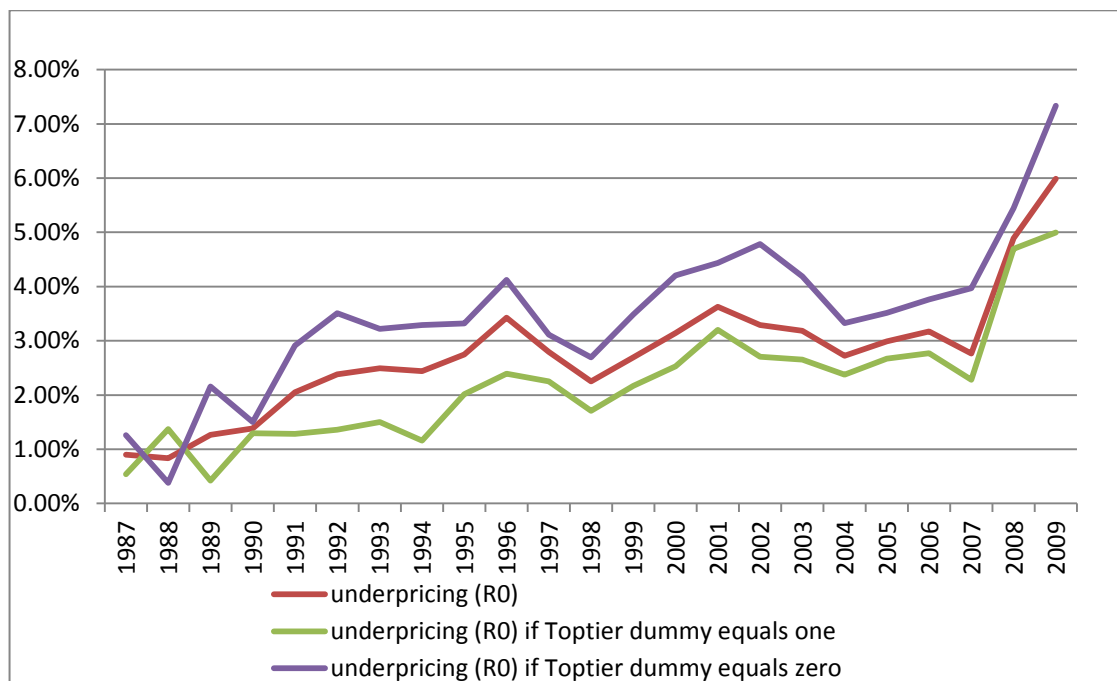


Figure 6-4 SEO underpricing by top-tier category

The conclusion from Bowen, Xia and Qiang (2008) strengthens the doubt. They hypothesised that analyst coverage can mitigate the information asymmetry and thereby reduce SEO underpricing. In their study, they used an offer date correction

method similar to Corwin's (2003). They defined dummy variable lead underwriter coverage as equal to one if an analyst from the lead underwriter team covered the issuer in the year prior to the offer. They also defined a dummy variable high-ability analyst coverage that equalled one if at least two analysts following the issuer in the year prior to the SEO were *Institutional Investor* All-American team analysts or experienced analysts⁷⁵. Both the variables had statistically negative effects on SEO underpricing.

In our study, we define the dummy variable *Toptier* analyst in the same way as Mola and Loughran (2004). Figure 6-4 presents SEO underpricing by top-tier category. Issues underwritten by banks with top-tier analysts are less underpriced than others. Given that the majority of banks with high reputation rankings actually have top-tier analyst teams, this result is reasonable and is consistent with Bowen, Xia and Qiang (2008).

6.2.5. NASDAQ Dummy and Pre-offer Price

Two factors are often used as control factors in studies of SEO underpricing. Both factors usually have statistically significant effects on SEO underpricing. However, there are few theoretical explanations for these two factors, therefore, we categorise them as factors from empirical evidence.

⁷⁵ In Bowen et al. (2008), an analyst is considered to be an experienced analyst in a given year if the general experience of the analyst is in the top quartile of analysts' general experience in that year. An analyst's general experience is measured as the number of quarters between the first earnings forecast issued by the analyst (for any firm) and the offer date of the SEO. The relative data are obtained from I/B/E/S Detailed Earnings Forecast file.

The first factor is the market where the share is listed. Almost all studies on SEO underpricing document the differences in SEO underpricing between NASDAQ and NYSE firms. For instance, Corwin (2003) reported a 0.92% discount for NYSE offers and 2.72% discount for NASDAQ offers during his sample period. Altinkilic and Hansen (2003) also reported differences in underpricing between NYSE and NASDAQ offers. A possible explanation is the differences in characters between the two groups of issuers. NYSE issuers tend to be larger, more actively traded firms, while NASDAQ issuers are smaller firms with higher volatility of their shares.

Figure 6-5 illustrates the increase of SEO underpricing for both NASDAQ and NYSE issues. The increase of NASDAQ issues is more rapid than that of NYSE issues. The changing composite hypothesis suggests that the increase in SEO underpricing is caused by the increase of the ratio of NASDAQ issues to all issues. However, as both NASDAQ and NYSE issues experienced increase in SEO underpricing, the changing composite hypothesis obviously cannot fully explain the increase of SEO underpricing.

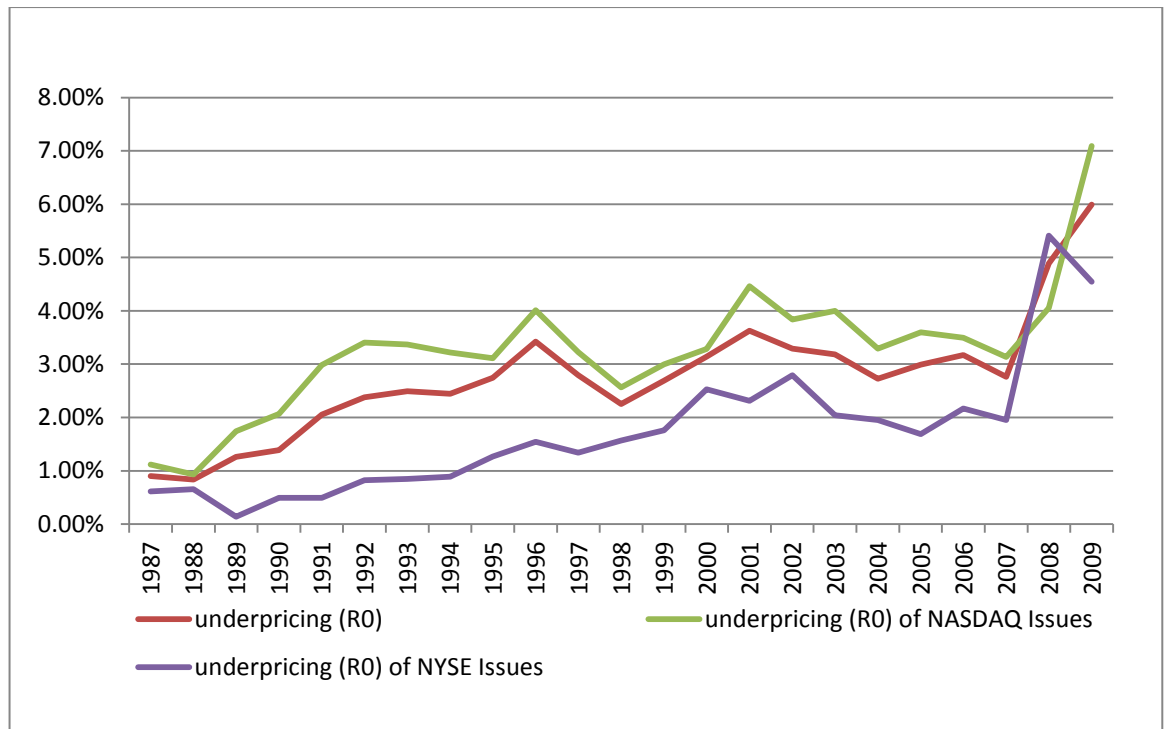


Figure 6-5 SEO underpricing by exchange category

The other factor is the price of the underlying shares. Nearly all studies of SEO underpricing suggest preoffer price is an important control factor in the regression analysis. One possible explanation is that offer price is often set at a level which gives a relatively small range of difference between offer price and price on the day prior to the offer. However, there is also no formal hypothesis about this factor. Corwin (2003) suggests that for issues with lower preoffer prices, the practice of setting the offer price at integer would have more effect on SEO underpricing. Butler et al. (2005) also mention that institutions prefer to shun low price shares, making it more difficult for underwriters to place low price shares. The results of empirical tests (e.g., Corwin, 2003; Kim and Park, 2005) suggest that preoffer price has significantly negative effects on SEO underpricing.

6.3. Descriptive Statistics

Table 6-2 Definitions of explanatory variables

RAProceeds90SEO	the ratio of aggregate SEO proceeds over the 90 trading days ending 1 day before the offer to the overall market capitalisation prior to the offer day.
MarketVolatility	the standard deviations of daily returns, computed using equal-weighted portfolios of all firms listed on NYSE/AMEX/NASDAQ/ARCA for the 21-trading-day returns ending one day before the offer day.
Market250	the proxy of liquidity shocks caused by market decline, $\text{MarketN} = \text{MarketReturnN} * D_{\text{market}}$, where MarketReturnN is the return on CRSP index over the prior N trading days and D_{market} equals one if $\text{MarketReturnN} > 0$ and zero otherwise.
Volatility	the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer
MarketCap	the logged pre-issue market capitalization, measured as the price multiplied by the total number of shares outstanding at the market close before the offer.
CARPos(Neg)	as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is positive (negative), where market return is defined as the return on the CRSP value weighted index
LnPrice	LnPrice is the logarithm of closing price on the day prior to the offer
CLUSTER	a dummy variable equal to one if the offer price is set at integer and equal to zero otherwise
CloseBidDiffNY	CloseBidDiffNY is (closing transaction price-closing bid quote)/closing transaction price and is zero if the issuer is listed on NYSE
CloseBidDiffNas	CloseBidDiffNas is (closing transaction price-closing bid quote)/closing transaction price and is zero if the issuer is listed on NASDAQ
NASDAQDummy	a dummy variable equal to one if the issuer is listed on Nasdaq and zero otherwise
Underwriter	a dummy equals one if one of the lead underwriters has the reputation rank equal to or greater than 8 and zero otherwise. The ranking is made by Ritter and available on http://bear.warrington.ufl.edu/ritter/ipodata.htm
Toptier	a dummy equal to one if the SEO underwriter (book manager) has an analyst group ranked among the top 10 groups selected by Institutional Investor each October of the prior calendar year
Reloffersize	the ratio of the No. of shares offered to the total No. of outstanding shares prior to the offer

Table 6-2 presents the definitions of all explanatory variables. The first three variables are proxies of liquidity shocks and the remaining variables are control variables that have been employed in the literature. Due to data limitations⁷⁶, for variables *CloseBidDiffNY* and *CloseBidDiffNas*, there are only 4761 observations and there are

⁷⁶ Some bid and ask data are missing in CRSP, especially for data before the 1990s.

5339 observations for variable *Volatility*, whilst for others there are 5347 observations.

In sum, there are 4756 SEOs without any missing value for all explanatory variables.

Table 6-3 Summary statistics for SEOs

	Means of All issues (N=4756)	Means of NYSE Issues (N=1326)	Means of NASDAQ Issues (N=3430)	p-value
Underpricing	3.04%	2.22%	3.35%	0.0000
MarketCap	19.89	21.04	19.45	0.0000
Volatility	3.75%	2.77%	4.12%	0.0000
CARPos	2.27%	1.92%	2.41%	0.0035
CARNeg	-4.24%	-3.24%	-4.63%	0.0000
LnPrice	3.04	3.23	2.96	0.0000
CloseBidDiff	0.89%	0.47%	1.06%	0.0000
Reloffersize	20.39%	14.98%	22.49%	0.0000
Underwriter	72.96%	89.74%	66.47%	0.0000
Toptier	52.44%	81.00%	41.40%	0.0000
Cluster	36.19%	28.51%	39.15%	0.0000
The sample includes 4756 SEOs from the period 1987-2009. The definition of the variables can be found at Table 6-2. The p-value is from a test of the restriction that means are equal across market based on an analysis of variance.				

Table 6-3 provides a general description for all issues, NYSE issues and NASDAQ issues⁷⁷. We can observe clear differences between NYSE and NASDAQ issues. NASDAQ issues are generally smaller in terms of prior closing price, market capitalisation and expected proceeds. They are underwritten by less prestigious banks more frequently. Shares of NASDAQ issues have higher volatility than shares of NYSE issues. Moreover, NASDAQ issues often have larger relative offer size than NYSE issues and setting offer prices at integer is also more popular among NASDAQ

⁷⁷ We only include SEOs without missing values for all explanatory variables. Therefore there are only 4756 SEOs in Table 6-3

issues than NYSE issues. Among all issues, around 40% of all NASDAQ issues have integer offer prices while about 30% of all NYSE issues have integer offer prices.

Table 6-4 Underpricing by category

Panel A Underpricing				
	Low			High
Quartile	1	2	3	4
MarketCap	4.01%	3.22%	2.51%	2.40%
Volatility	1.70%	2.63%	3.57%	4.24%
LnPrice	4.94%	2.92%	2.29%	1.99%
CAR5	3.43%	2.61%	2.54%	3.56%
Reloffersize	2.56%	2.76%	3.05%	3.78%
RAProceedsSEO90	2.83%	2.78%	2.77%	3.76%
MarketVolatility	2.36%	2.77%	2.84%	4.18%
Panel B Underpricing				
	if Market250=0		if Market250<0	
Underpricing 1987-2007	2.77% (3883 observations)		4.21% (873 observations)	
Underpricing 1987-1995	2.38% (1414 observations)		1.97% (85 observations)	
Underpricing 1996-2001	2.84% (1454 observations)		3.83% (203 observations)	
Underpricing 2002-2009	3.22% (1015 observations)		4.66% (585 observations)	
The definitions of the variables can be found at Table 6-2. The sample includes 4756 SEOs from the period 1987-2009.				

Table 6-4 presents two panels with univariate analysis. For each control variable, Panel A lists the average underpricing in each quartile. Volatility and relative offer size seem to be positively associated with underpricing while market capitalisation, pre-offer price seem to be negatively related to underpricing. The U-shape for cumulative abnormal return is consistent with the empirical evidence that underpricing is positively related to absolute value of CAR. All of this is consistent with the literature.

Regarding proxies of liquidity shocks, the magnitudes of average underpricing in the first three quartiles remains stable for *RAProceeds90SEO* and *MarketVolatility* seems to be positively associated with underpricing. In Panel B, *Market250* represents the liquidity shocks. The average underpricing when *Market250* is less than zero is larger than that when *Market250* is zero. For all issues, issues offered during market downturn have higher underpricing (4.21%) than others (2.77%).

Table 6-5 presents descriptive statistics of all the control variables by subperiods. Most control variables did not change consistently over the three subperiods. As for *Volatility* and *LnPrice*, there is an increase in the value from Period 1 to Period 2 and then a decrease from period 2 to period 3. Both *CARPos(Neg)* and *CloseBidDiffNY(Nas)* have similar patterns. As discussed earlier, *CLUSTER* represents the practice of setting offer prices at integer. In Period 1, 32.76% of issues have integer offer prices. This ratio increases to 46.11% in period 2. Apparently, setting offer price at integer contributed to the increase of SEO underpricing over Period 1 and Period 2, however the ratio decreases to 29.13% in Period 3, indicating that other factors may have effects on SEO underpricing over time.

Additionally, relative offer size is relatively stable during Period 1 and Period 2. The previous univariate analysis already suggests that both variables are positively related to SEO underpricing. The *underwriter* dummy, which represents the reputation of underwriters, is almost constant over time, indicating that the ratio of issues underwritten by high reputation underwriters is stable over time. The ratio of issues underwritten by banks with top-tier analyst teams increases from period 2 to period 3, indicating that more offers are underwritten by banks with a top-tier analyst team.

Table 6-5 Descriptive statistics of explanatory variables by subperiods

	1 (1987-1995)	2 (1996-2001)	3 (2002-2009)	P-value(2)-(1)	P-value(3)-(2)
Volatility	3.42%	4.40%	3.38%	0.0000	1.0000
	3.12%	3.74%	2.90%	0.0000	0.0000
MarketCap	19.06	20.03	20.54	0.0000	0.0000
	18.98	19.92	20.35	0.0000	0.0000
CARPos	1.77%	2.65%	2.34%	0.0000	0.9347
	-	-	-		
CARNeg	-3.67%	-5.27%	-3.71%	1.0000	0.0000
	-	-	-		
LnPrice	2.91	3.27	2.90	0.0000	1.0000
	2.94	3.27	2.98	0.0000	0.0000
CLUSTER	32.76%	46.11%	29.13%	0.0000	1.0000
	-	-	-		
CloseBidDiffNY	0.13%	0.20%	0.06%	0.0000	1.0000
	-	-	-		
CloseBidDiffNas	1.54%	0.69%	0.11%	1.0000	1.0000
	-	-	-		
NASDAQDummy	81.72%	76.10%	59.06%	0.9999	1.0000
	-	-	-		
Underwriter	69.78%	77.61%	71.13%	0.0000	1.0000
	-	-	-		
Toptier	41.69%	49.97%	65.06%	0.0000	0.0000
	-	-	-		
Reloffersize	22.81%	21.06%	17.44%	0.9984	1.0000
	19.97%	17.36%	14.07%	0.0000	0.0000
No. of Obs.	1499	1657	1600		
The sample includes 4756 SEOs from the period 1987-2009. The definitions of these variables are listed in Table 6-2. Means (medians) are listed in the first (second) line for each variable. p-values for difference within subsample means (medians) are from standard t-tests (Wilcoxon rank-sum test).					

6.4. Regression Results of SEO Underpricing

In this section, the multivariate tests are conducted. The base model is listed below by including all control variables discussed earlier, then proxies of liquidity shocks are incorporated and comprehensive analysis is conducted.

$$\begin{aligned} \text{Underpricing} = & \beta_0 + \beta_1 \text{MarketCap} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} + \\ & \beta_6 \text{CLUSTER} + \beta_7 \text{CloseBidDiffNY} + \beta_8 \text{CloseBidDiffNas} + \beta_9 \text{NASDAQDummy} + \\ & \beta_{10} \text{Underwriter} + \beta_{11} \text{Toptier} + \beta_{12} \text{Reloffersize}. \end{aligned} \quad (6.1)$$

We include three variables of liquidity shocks into the base model and test the effects of these variables on underpricing. Panel A and Panel B in Table 6-6 report the results from estimating multiple regressions using different sets of variables across the 1987 to 2009 sample period. The only difference between the two panels is that Panel B includes year dummies in all regressions.

In Panel A, proxies of liquidity shocks from Model 2 to Model 4 are consistent and have the expected sign and the coefficients of these proxies of liquidity shocks are statistically significant at conventional levels. In Model 5, when three proxies are included, only *MarketVolatility* is statistically and positively associated with the SEO underpricing. *Market250* exhibits a weak negative link with SEO underpricing while there seems to be no incremental link between *RAProceeds90SEO* and SEO underpricing.

In Panel B, year dummies are added into the regressions. Although proxies of liquidity shocks still have the expected signs in Model 2 to Model 5, coefficients of

RAProceeds90SEO and *Market250* are statistically insignificant. Comparison of these results with those in Panel A suggests that the effects of *RAProceeds90SEO* and *Market250* might be captured by year dummies. Only the *MarketVolatility* coefficient is significant. The *MarketVolatility* coefficient indicates that, holding other things equal, underpricing will increase by 0.5% if *MarketVolatility* increases by about 1%.

Table 6-6 OLS Regression results for SEO underpricing

Panel A					
	1	2	3	4	5
MarketCap	0.0067*** (12.25)	0.0066*** (12.14)	0.0058*** (10.48)	0.0050*** (9.01)	0.0050*** (8.95)
Volatility	0.2248*** (10.00)	0.2028*** (8.93)	0.1898*** (8.40)	0.1650*** (7.30)	0.1618*** (7.12)
CARPos	0.0767*** (7.81)	0.0746*** (7.61)	0.0743*** (7.63)	0.0731*** (7.56)	0.0727*** (7.52)
CARNeg	-0.0152* (-1.67)	-0.0090 (-0.99)	-0.0142 (-1.58)	-0.0028 (-0.31)	-0.0035 (-0.38)
LnPrice	-0.0212*** (-23.92)	-0.0206*** (-23.26)	-0.0191*** (-21.18)	-0.0187*** (-21.03)	-0.0185*** (-20.56)
CLUSTER	0.0122*** (12.44)	0.0120*** (12.26)	0.0119*** (12.19)	0.0116*** (12.01)	0.0116*** (11.98)
CloseBidDiffNY	0.3642*** (2.88)	0.3970*** (3.15)	0.4764*** (3.78)	0.4866*** (3.90)	0.5017*** (4.01)
CloseBidDiffNas	0.5445*** (15.30)	0.5363*** (15.11)	0.5717*** (16.16)	0.5962*** (16.93)	0.5950*** (16.81)
NASDAQDummy	0.0041*** (2.87)	0.0052*** (3.58)	0.0060*** (4.14)	0.0060*** (4.22)	0.0064*** (4.42)
Underwriter	-0.0080*** (-6.19)	-0.0077*** (-5.98)	-0.0073*** (-5.66)	-0.0061*** (-4.75)	-0.0061*** (-4.78)
Toptier	-0.0008 (-0.64)	-0.0006 (-0.52)	-0.0009 (-0.78)	-0.0010 (-0.83)	-0.0010 (-0.82)
Reloffersize	0.0130*** (3.98)	0.0133*** (4.09)	0.0126*** (3.89)	0.0119*** (3.70)	0.0120*** (3.73)
RAProceeds90SEO		0.0032*** (5.93)			0.0004 (0.64)
Market250			-0.0593*** (-9.31)		-0.0144* (-1.73)
MarketVolatility				1.4704*** (12.76)	1.2774*** (8.64)
Constant	-0.0579*** (-5.54)	-0.0620*** (-5.94)	-0.0480*** (-4.60)	-0.0411*** (-3.96)	-0.0413*** (-3.95)
Year Dummy	No	No	No	No	No
N	4756	4756	4756	4756	4756
Adjusted R ²	0.2462	0.2516	0.2596	0.2711	0.2715

Panel B					
	1	2	3	4	5
MarketCap	0.0014** (2.36)	0.0014** (2.41)	0.0014** (2.34)	0.0014** (2.30)	0.0014** (2.38)
Volatility	0.1769*** (7.65)	0.1747*** (7.54)	0.1753*** (7.52)	0.1681*** (7.22)	0.1701*** (7.29)
CARPos	0.0660*** (6.94)	0.0659*** (6.93)	0.0659*** (6.93)	0.0664*** (6.99)	0.0668*** (7.03)
CARNeg	-0.0034 (-0.38)	-0.0020 (-0.22)	-0.0033 (-0.36)	-0.0014 (-0.16)	-0.0003 (-0.03)
LnPrice	-0.0151*** (-15.58)	-0.0151*** (-15.60)	-0.0151*** (-15.57)	-0.0150*** (-15.51)	-0.0151*** (-15.52)
CLUSTER	0.0113*** (11.90)	0.0112*** (11.86)	0.0112*** (11.88)	0.0112*** (11.80)	0.0112*** (11.81)
CloseBidDiffNY	0.6698*** (5.29)	0.6726*** (5.31)	0.6719*** (5.30)	0.6632*** (5.24)	0.6562*** (5.18)
CloseBidDiffNas	0.7204*** (19.91)	0.7210*** (19.93)	0.7202*** (19.90)	0.7195*** (19.91)	0.7207*** (19.94)
NASDAQDummy	0.0055*** (3.86)	0.0056*** (3.94)	0.0056*** (3.90)	0.0058*** (4.07)	0.0057*** (3.97)
Underwriter	-0.0026** (-2.04)	-0.0026** (-2.02)	-0.0026** (-2.04)	-0.0025** (-1.97)	-0.0025** (-1.96)
Toptier	-0.0018 (-1.58)	-0.0018 (-1.58)	-0.0018 (-1.58)	-0.0018 (-1.54)	-0.0018 (-1.54)
Reloffersize	0.0034 (1.08)	0.0036 (1.13)	0.0035 (1.10)	0.0038 (1.20)	0.0038 (1.21)
RAProceeds90SEO		0.0011 (1.40)			0.0008 (1.04)
Market250			-0.0046 (-0.52)		0.0170 (1.54)
MarketVolatility				0.4444*** (3.14)	0.5405*** (3.26)
Constant	0.0004 (0.04)	-0.0017 (-0.15)	0.0005 (0.05)	-0.0010 (-0.09)	-0.0035 (-0.31)
Year Dummy	Yes	Yes	Yes	Yes	Yes
N	4756	4756	4756	4756	4756
Adjusted R ²	0.3079	0.3081	0.3078	0.3092	0.3094

Underpricing is defined as $((P-OP)/P)*100$, where P is the prior offer closing price and OP is the offer price. Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. MarketCap is the logged pre-issue market capitalization, measured as the price multiplied by the total number of shares outstanding at the market close before the offer. CARPos (CARNeg) is defined as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is negative (positive), where market return is defined as the return on the CRSP value weighted index. CLUSTER is a Dummy equal to one if the offer price is set at integer. CloseBidDiffNYSE (CloseBidDiffNas) is Closing transaction price-closing bid quote/closing transaction price and is zero if the issuer is list on NASDAQ (NYSE). NASDAQDummy is a dummy variable equal to one if the issuer is list on NASDAQ. Toptier is a dummy equal to one if the SEO underwriter (book manager) has an analyst group ranked among the top 10 groups selected by Institutional investor each October of the prior calendar year. Underwriter is a dummy equals one if one of the lead underwriters has the reputation rank equal to or greater than 8 and zero otherwise. The ranking is made by Ritter and available on <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. Reloffersize is the ratio between the shares offered to the outstanding shares prior to the offer. RAProceeds90SEO is the ratio of aggregate SEO proceeds over the 90 trading days ending 1 day before the offer to the overall market capitalization prior to the offer day. MarketVolatility is the standard deviations of daily returns, computed using equal-weighted portfolios of all firms listed on NYSE/AMEX/NASDAQ/ARCA for the 21-trading-day returns ending one day before the offer day. Market250 the proxy of liquidity shocks caused by market decline, $Market250 = MarketReturn250 * D_{market}$, where MarketReturn250 is the return on CRSP index over the prior 250 trading days and D_{market} equals one if MarketReturn250 > 0 and zero otherwise. The value of t statistics is in brackets. ***, **, and * represent 1% 5% and 10% significance, respectively.

Among other variables in Panel A and Panel B, all variables are of the expected sign except two, namely *MarketCap* and *Top-tier*. *MarketCap* is the proxy of information asymmetry. SEO made by firms with large market capitalisations suffer less from the problem of information asymmetry. Therefore, the expected sign for *MarketCap* should be negative. In our regressions, however, all coefficients of *MarketCap* are significantly positive. This result indicates that SEOs suffer less from information asymmetry than IPOs, which is consistent with the literature (e.g. Chemmanur et al., 2009).

Regarding *Top-tier* analyst, this variable equals one if one of lead underwriters has a top-tier analyst team ranked by Institutional Investors in the last year, and zero otherwise. The coefficients of this variable in all regressions are insignificantly negative. The results are consistent with what we found in Chapter Five. Again, there is no evidence suggesting that issues underwritten by a syndicate with a top-tier analyst team would be underpriced more than others, *ceteris paribus*. However, an insignificant coefficient of the *Top-tier* variable does not necessarily mean that there is no evidence of investment banking power. What we find here only suggests that the variable *Top-tier* dummy may be not an appropriate proxy of investment banking power in the case of SEO underpricing.

CLUSTER equals one if the offer price is set at integer, and zero otherwise. In all regressions, the coefficients on *CLUSTER* are positively significant. For instance, in Model 5 Panel B, the coefficient suggests that if an issue is priced at integer, the SEO underpricing will be 1.12% higher than one with a non-integer offer price, all else being equal. As for the pricing practice of setting offer prices at closing bid, both

CloseBidDiffNY and *CloseBidDiffNas* have significant coefficients with the expected sign. In model 1-5 Panel B, the *CloseBidDiffNY* coefficient is around 0.66, while the *CloseBidDiffNas* coefficient is around 0.7, suggesting that the practice has substantial effects on SEO underpricing in our sample.

Volatility, *CARPos* and *LnPrice*, *NASDAQDummy*, and *Underwriter* all have significant coefficients with expected signs in all regressions. These results are in line with recent studies such as Chemmanur et al. (2009), Huang and Zhang (2011) and Autore (2011). The coefficients of *CARNeg* and *Reloffersize* are insignificant despite having the expected signs. This result is consistent with Chemmanur et al. (2009)

6.5. The Behaviour of SEO Underpricing

After discussing the regression results, we turn to the behaviour of SEO underpricing over our sample period from 1987 to 2009. In our model, we found some mixed evidence regarding the liquidity shocks hypothesis. One proxy, *MarketVolatility*, is significantly and positively associated with SEO underpricing in all sets of regressions, while two others, *Market250* and *RAProceeds90SEO*, have insignificant coefficients when year dummies are included in regressions. In this section, we use model (6.2) to estimate coefficients on the year dummy variables, controlling for issue characteristics, firm characteristics, liquidity shocks caused by market conditions.

$$\begin{aligned} \text{Underpricing} = & \beta_0 + \beta_1 \text{MarketCap} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} + \\ & \beta_6 \text{CLUSTER} + \beta_7 \text{CloseBidDiffNY} + \beta_8 \text{CloseBidDiffNas} + \beta_9 \text{NASDAQDummy} + \\ & \beta_{10} \text{Underwriter} + \beta_{11} \text{Toptier} + \beta_{12} \text{Reloffersize} + \beta_{13} \text{RAProceedsSEO90} + \beta_{14} \text{Market250} + \\ & \beta_{15} \text{MarketVolatility}. \end{aligned} \tag{6.2}$$

The estimation method proposed by Chambers and Dimson (2009) has already been adopted in Chapter Five. First of all, all explanatory variables except for year dummies were demeaned. Then, the coefficients of year dummies were calculated using a regression with underpricing and all demeaned explanatory variables. Under this method, in model (6.2) each year dummy coefficient represents the level of underpricing experienced in a given year by an SEO with characteristics in line with average values for the sample.

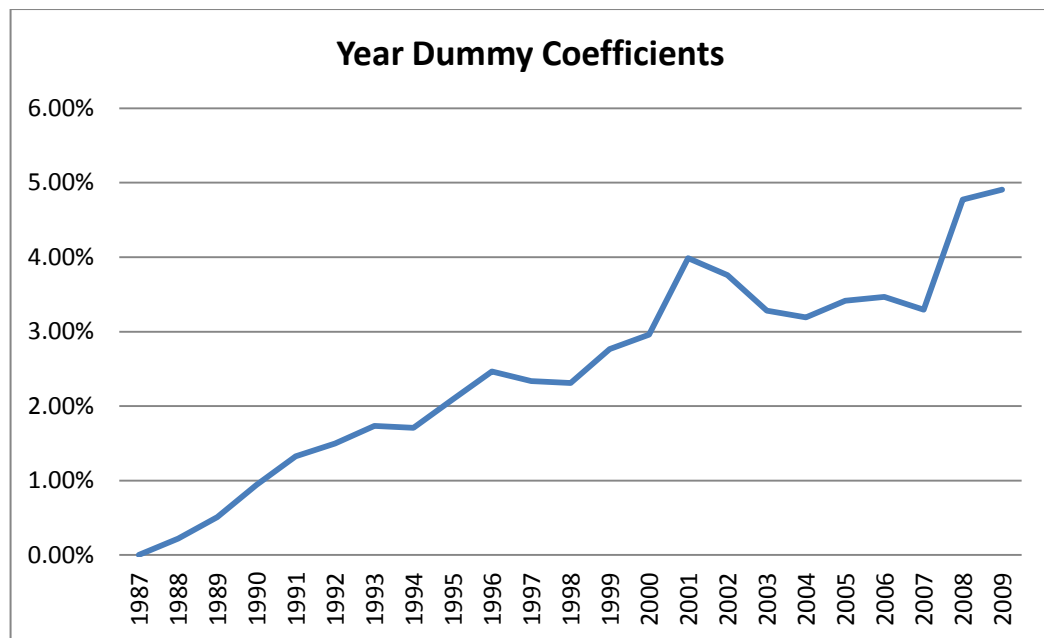


Figure 6-6 Year dummy coefficients in regression of underpricing on control variables

Figure 6-6 illustrates the time series of year dummy coefficients from 1987 to 2009. We can observe an evident upward shift of SEO underpricing over time after controlling for issue and firm characteristics. If we divide the sample period into two subperiods, namely 1987 to 1997 and 1998 to 2009, we can weigh the coefficients by the number of SEOs in each year and calculate the number-weighted means of the

year dummy coefficients of the two subperiods. The weighted means of the year dummy coefficients for the two subperiods are 1.80% and 3.49%: an increase of 1.69%.

6.6. Effects of Rounding Offer Price at Integer

As mentioned earlier, *CLUSTER* dummy equals one if the offer price is set at integer and zero otherwise. *CLUSTER* is the most economically and statistically significant variable in Table 6-6. The coefficient of *CLUSTER* is around 110 bps. This result means that if the offer price is set at integer, on average the underpricing is 1.1% higher than others, ceteris paribus. In Section 6.5., the demeaned *CLUSTER* is employed as the control variable in the regression. However, the variable *CLUSTER* only reflects the fact that the offer price is set at integer. For offers with integer offer prices equal to the prior closing price, the underpricing is zero.

6.6.1. Lower Integer Offer Price and Upward Shift of SEO Underpricing

Among the cases of integer offer price, only setting offer prices at next lower integer or other lower integer contributes to the increase of SEO underpricing. Therefore, one possible explanation for the upward shift of SEO underpricing is that more offers are priced at next lower or other lower integer.

To examine this explanation, we can divide the sample into two subsamples. One only includes offers with next lower or other lower integer offer prices, the other has the remaining offers. For each sample, we estimate the coefficients of year dummy using the method proposed by Chambers and Dimson (2009). If the coefficients of year

dummy remain stable over time for the second sample, we could attribute the reason for the upward shift to the prevalence of pricing offers at next lower or other lower integers.

$$\begin{aligned} \text{Underpricing} = & \beta_0 + \beta_1 \text{MarketCap} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} + \\ & \beta_6 \text{CloseBidDiffNY} + \beta_7 \text{CloseBidDiffNas} + \beta_8 \text{NASDAQDummy} + \beta_9 \text{Underwriter} + \\ & \beta_{10} \text{Toptier} + \beta_{11} \text{Reloffersize} + \beta_{12} \text{RAProceedsSEO90} + \beta_{13} \text{Market250} + \\ & \beta_{14} \text{MarketVolatility}. \end{aligned} \quad (6.3)$$

The regression model (6.3) is employed for two subsamples. In the first sample, only offers with next lower or other lower integer offer prices are included. Those offers that have integer offer prices equal to prior close prices are included in the second sample. The first sample has 1496 SEOs. For the second sample, we have 3260 SEOs. We graph the year dummy coefficients for two samples in Figure 6-7 and Figure 6-8 respectively.

Similar to Figure 6-6, both Figure 6-7 and Figure 6-8 show an upward shift in SEO underpricing. The difference between Figure 6-7 and Figure 6-8 is that coefficients in Figure 6-7 are more volatile than in Figure 6-8. The comparison of Figure 6-7 and Figure 6-8 suggests that offers with lower integer offer prices and the remaining offers share a similar upward shift in SEO underpricing over the sample period.

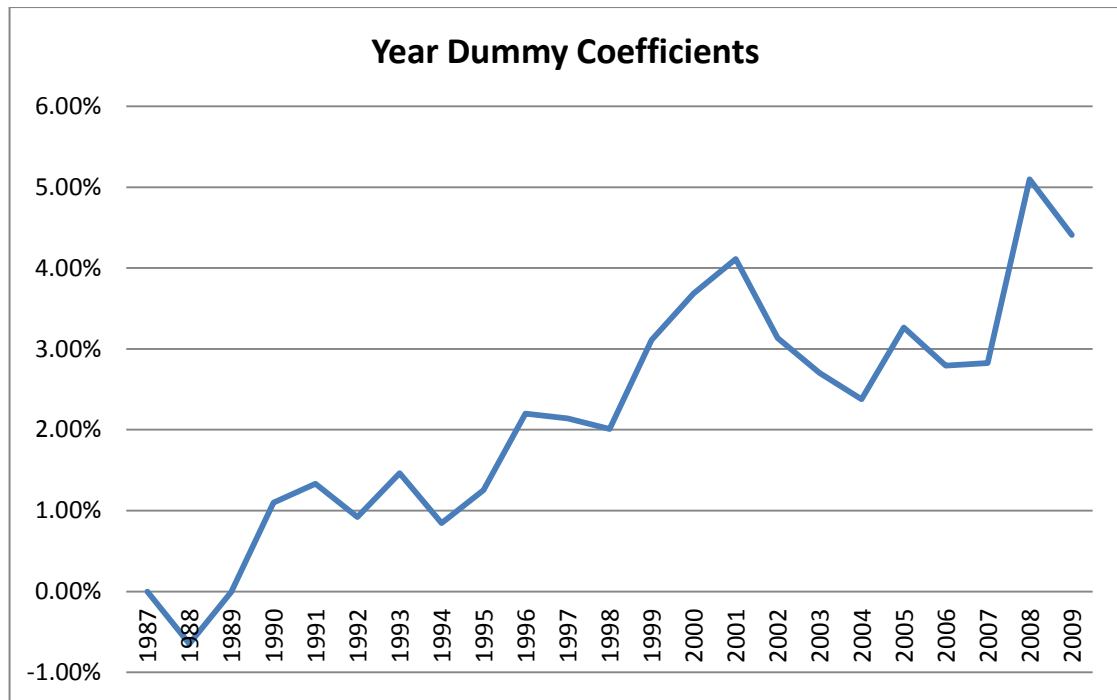


Figure 6-7 Year dummy coefficients for the subsample that only includes SEOs that are priced at lower integers

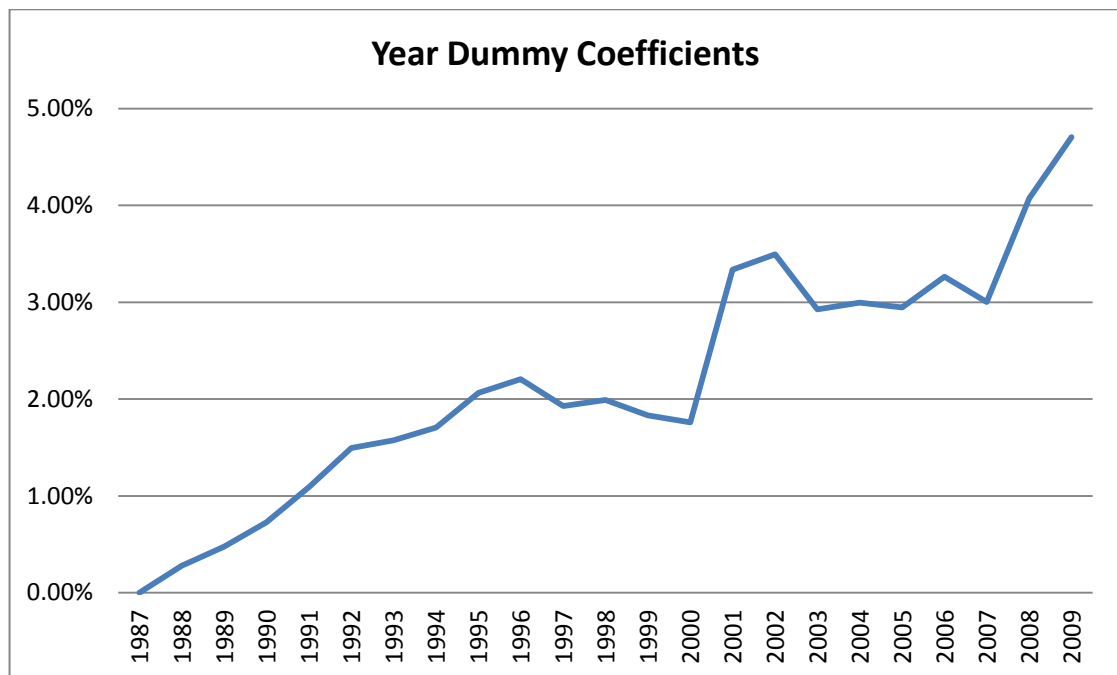


Figure 6-8 Year dummy coefficients for the subsample that only includes SEOs that are not priced at lower integers

If we divide the sample period into two subperiods, 1987 to 1997 and 1998 to 2009, we can weigh the coefficients by the number of SEOs each year and calculate the number-weighted means of SEO underpricing for two subperiods. Figure 6-7 shows the coefficients of year dummy for the sample of SEOs with next lower and other lower integer offer prices. The number-weighted means for the subperiod 1987 to 1997 and subperiod 1998 to 2009 are 1.56% and 3.36% respectively, reflecting an increase of 1.80%. In Figure 6-8, we have the number-weighted mean equal to 1.59% for the subperiod 1987 to 1997, and 3.06% for the subperiod 1998 to 2009: an increase of 1.47%.

In sum, Figure 6-8 suggests that for those offers that are not priced at next lower or other lower integer price, there is still an upward shift in SEO underpricing, which is similar to offers with next lower integer offer prices. For the 3260 offers in Figure 6-8, setting offer prices at next lower or other lower integers seems not to be able to explain the upward shift in SEO underpricing.

6.6.2. Probit Analysis of Setting Offer Price at Lower Integers

As discussed in section 6.2.3.1., setting offer prices at next lower or other lower integers becomes more prevalent over our sample period. In this section, we analyse which factors could contribute to the likelihood of setting offer prices at lower integers. The probit model (6.4) is employed.

$$\begin{aligned}
 (Other)Lower\ Integer = & \beta_0 + \beta_1 MarketCap + \beta_2 Volatility + \beta_3 CARPos + \beta_4 CARNeg + \\
 & \beta_5 LnPrice + \beta_6 CloseBidDiffNY + \beta_7 CloseBidDiffNas + \beta_8 NASDAQDummy + \\
 & \beta_9 Underwriter + \beta_{10} Toptier + \beta_{11} Reloffersize + \beta_{12} RAProceedsSEO90 + \beta_{13} Market250 + \\
 & \beta_{14} MarketVolatility + \beta_{15} MTH + \beta_{16} DecimalDummy.
 \end{aligned} \tag{6.4}$$

The probit model (6.3) is developed from model (6.2). The main difference between them is that we add two explanatory variables, *MTH* and *DecimalDummy*. *MTH* is a time variable that equals one in January 1987 and increments by one each succeeding month. *DecimalDummy* reflects the conversion of the reporting of stock prices from fractions to decimals on April 9, 2001 in the US market. *DecimalDummy* is equal to one if the offer is offered on the date after April 9, 2001, and zero otherwise.

In Model 1 Table 6-7, the dependent variable is OTHER LOWER INTEGER dummy. This binary variable is equal to one if the offer price is set at other lower integers relative to the prior closing price, and zero otherwise. For instance, assuming the prior closing price of an issue is \$10.7, the OTHER LOWER INTEGER dummy is one if the offer price is set at \$9 or lower integers (\$ 8, 7, etc.). In Model 2, the dependent variable for this set is LOWER INTEGER dummy. The variable is set to one if the offer price is set at either next lower integer or other lower integers relative to the

prior closing price, and zero otherwise. Taking the above example again, the dummy is one if the offer price is set at \$10 or lower integers (\$9, 8, etc.).

Table 6-7 Logit regressions of other lower integer dummy variable/next lower or other lower integer dummy variable

	Model 1	Model 2
MarketCap	-0.0578* (-1.67)	-0.0470* (-1.78)
Volatility	7.7358*** (6.66)	4.6627*** (4.78)
CARPos	0.6616 (1.35)	0.0052 (0.01)
CARNeg	-1.7279*** (-3.60)	-1.6117*** (-4.23)
LnPrice	0.8076*** (13.38)	0.3336*** (7.92)
CloseBidDiffNY	2.2067 (0.26)	10.9481* (1.92)
CloseBidDiffNas	15.5743*** (7.93)	9.3123*** (6.00)
NASDAQDummy	0.1749** (2.03)	0.2493*** (3.91)
Underwriter	0.1012 (1.37)	0.1845*** (3.33)
Toptier	-0.1725** (-2.57)	-0.1987*** (-3.91)
Reloffersize	0.3466* (1.95)	0.3534*** (2.59)
MTH	0.0055*** (5.93)	0.0045*** (6.78)
Decimaldummy	-0.3687*** (-3.03)	-0.3648*** (-3.96)
RAProceeds90SEO	0.0108 (0.31)	-0.0096 (-0.36)
Market250	-0.7434 (-1.49)	-0.7821** (-2.04)
MarketVolatility	5.7693 (0.70)	3.7450 (0.56)
Constant	-4.1129*** (-6.63)	-1.7757*** (-3.76)
N	4756	4756
Pseudo R ²	0.1637	0.0586

In Model 1, the Dependent variable is Other Lower Integer Dummy which is equal to one if the offer price is set at the other lower integers relative to the prior closing price and zero otherwise. For instance, assuming the prior closing price of an issue is \$ 10.7, the OTHER LOWER INTEGER dummy is one if the offer price is set at \$ 9 or lower integers (\$ 8, 7, etc.). Panel B The Dependent variable is Next Lower Integer or Other Lower Integer Dummy which is equal to one if the offer price is set at either the next lower integer or other lower integers relative to the prior closing price and zero otherwise. For instance, assuming the prior closing price of an issue is \$ 10.7, the Next Lower Integer/OTHER LOWER INTEGER dummy is one if the offer price is set at \$ 10 or lower integers (\$ 9, 8, 7, etc.). Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. MarketCap is the logged pre-issue market capitalization, measured as the price multiplied by the total number of shares outstanding at the market close before the offer. CARPos (CARNeg) is defined as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is negative (positive), where market return is defined as the return on the CRSP value weighted index. CLUSTER is a Dummy equal to one if the offer price is set at integer. CloseBidDiffNYSE (CloseBidDiffNas) is Closing transaction price-closing bid quote/closing transaction price and is zero if the issuer is list on Nasdaq (NYSE). NASDAQDummy is a dummy variable equal to one if the issuer is list on Nasdaq. Toptier is a dummy equal to one if the SEO underwriter (book manager) has an analyst group ranked among the top 10 groups selected by Institutional investor each October of the prior calendar year. Underwriter is a dummy equals one if one of the lead underwriters has the reputation rank equal to or greater than 8 and zero otherwise. The ranking is made by Ritter and available on <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. Reloffersize is the ratio between the shares offered to the outstanding shares prior to the offer. RAProceeds90SEO is the ratio of aggregate SEO proceeds over the 90 trading days ending 1 day before the offer to the overall market capitalization prior to the offer day. MarketVolatility is the standard deviations of daily returns, computed using equal-weighted portfolios of all firms listed on NYSE/AMEX/NASDAQ/ARCA for the 21-trading-day returns ending one day before the offer day. Market250 the proxy of liquidity shocks caused by market decline, $\text{Market250} = \text{MarketReturn250} * D_{\text{market}}$, where MarketReturn250 is the return on CRSP index over the prior 250 trading days and D_{market} equals one if $\text{MarketReturn250} > 0$ and zero otherwise. White's heteroskedasticity-adjusted z-statistics are in parentheses. ***, **, and * represent 1%, 5% and 10% significance, respectively.

In Model 1 and Model 2 Table 6-7, the majority of variables have coefficients with the expected signs, and many of them are statistically significant at the conventional levels. For instance, the coefficients of *Volatility*, *CARNeg*, *LnPrice*, *NASDAQDummy*, and *CloseBidDiffNas* have the expected signs and are statistically significant. Some variables, such as *MarketCap* and *CARPos*, have insignificant coefficients in the two models.

In both models, the *Toptier* coefficients are significantly negative, suggesting that offers made by syndicates with top-tier analyst teams are less likely to be priced at lower integer offer prices. This result is consistent with that in Table 6-6. In Model 2, the underwriter coefficient is highly significant, with a sign which is inconsistent with the expectation. Almost all coefficients of liquidity shocks variables are insignificant, despite the fact that most of them have the expected signs. These results suggest that liquidity shocks caused by market conditions might not be a major concern when the underwriters decide to round the offer price.

The *DecimalDummy* has the expected sign and is significant at the 1% level in both models. The results show that the likelihood of setting offer prices at lower integers is reduced by the conversion of reporting stock price from fractions to decimals on April 9, 2001, *ceteris paribus*. The dummy variable *MTH* is of the expected sign and is statistically significant at the 1% level in both models. These results indicate that there is a trend over time for underwriters to set offer prices at next lower or other lower integer prices, all else being equal. The trend might be regarded as evidence of increasing investment banking power.

6.7. Discussions for the Upward Shift in SEO Underpricing

In Section 6.5, annual underpricing dummies indicated that after controlling for changing risk composition, price practice, market conditions, the influence of underwriter reputation and analyst coverage, there was a substantial rise in annual underpricing over our sample period from 1987 to 2009. The results indicate that other influences might contribute to the rise in annual SEO underpricing. In this section, we borrow the investment banking power hypothesis from the literature and argue that the upward shift is the result of increasing investment banking power.

A variety of investment banking power hypotheses have been proposed in the literature. In the US market, Chen and Ritter (2000) found that in the period from 1995 to 1998, more than 90% of deals raising \$20-80 million had spreads of exactly 7%, three times the proportion of a decade earlier. They argue that several features in the IPO underwriting market, namely analyst coverage, buy recommendations and

underwriter prestige, enabled US underwriters to set spreads (direct IPO costs) above the competitive level.

Loughran and Ritter (2004) proposed the analyst lust hypothesis to explain the increase of IPO underpricing over the period from 1980-2003. They argue that each issuer faces a local oligopoly of underwriters because 1) issuers placed more importance on hiring a lead underwriter with a highly ranked analyst team than before and 2) there is a limited number of all-star analysts. Liu and Ritter (2011) argue that the industry structure of equity underwriting is best characterised as a series of local oligopolies if issuers care about non-price dimensions of underwriting, and they find that a limited number of underwriters that can provide these non-price dimensions will acquire some market power and earn rents on the IPOs.

After examining the behaviour of UK IPO underpricing over the very long period from 1917 to 1986, Chambers and Dimson (2009) hypothesised that investment banks exerted market power in UK IPOs after 1945, which could be regarded as a possible explanation for the rise in IPO underpricing over their sample period. They argue that despite the fact that issue methods emerged that mitigated underpricing before the Big Bang, banks together with institutional investors, stuck with the traditional fixed price method before the Big Bang and consequently were able to benefit by underpricing IPOs more⁷⁸.

⁷⁸ The Big Bang refers to the deregulation of fixed brokerage commissions and the termination of restrictions on membership on the LSE.

In our study, we hypothesise that the increase in the market power of investment banks could contribute to the rise in annual underpricing dummies. As the structure of the underwriting industry transfers from a competitive market to an oligopoly market, underwriters are able to exert their market power to make issuers leave more money on the table.

We have three findings related to the investment banking power hypothesis. First, different from the case of IPOs, we find no evidence that underwriters use analyst coverage as a non-price dimension to increase SEO underpricing. The results indicate that other non-price dimensions might be employed by underwriters to retain their oligopoly status. Second, we find that after controlling for other factors, the practice of setting offer prices at next or other lower integers has become more prevalent over time, which could be regarded as evidence for the increase of investment banking power. Last but not least, in our subsample tests, we find that the subsample of SEOs that are not priced at lower integer offer prices exhibited a rise in the annual underpricing dummies. The pattern of the annual underpricing dummies is similar to that of the subsample of SEOs with lower integer offer prices. This result indicates that the practice of setting offer prices at lower integers cannot fully explain the upward shift in SEO underpricing over time.

6.8. Chapter Summary

In this chapter, we hypothesised that certain market conditions could cause liquidity shocks that would increase SEO underpricing consequently. We proposed three scenarios of market conditions, namely aggregate issues with large volume, large

market decline and market volatility. Empirical results show that market volatility is significantly and positively related to SEO underpricing after controlling for other factors.

We included three proxies of liquidity shocks into our regression model and employed an estimation method proposed by Chambers and Dimson (2009) to examine the behaviour of SEO underpricing over our sample period from 1987 to 2009. We found that after controlling for changing risk composition, price practice, market conditions and the influence of underwriter reputation and analyst coverage, there was still an upward shift in SEO underpricing over the sample period. The number-weighted mean of the year dummy coefficients for 1987-1997 was 1.80% while it was 3.49% for 1998-2009.

We divided the sample into two subsamples based on whether the offer price was set at lower integer price or not. In both subsamples, we observed similar patterns of year dummy coefficients. This result indicates that setting offer prices at lower integers cannot fully explain the upward shift of annual underpricing dummies. Moreover, by employing a probit model, we found that the practice of setting offer prices at lower integers has become more prevalent over time, *ceteris paribus*.

We borrowed the investment banking power hypothesis from the literature and argued that the upward shift of SEO underpricing over the sample period could be explained by the increase of investment banking power. As the industry structure of underwriting transfers from a competitive market to an oligopoly market, banks use

non-price dimensions to gain market power and consequently increase SEO underpricing.

CHAPTER 7: LIQUIDITY AND SEO FLOTATION COST

As discussed in the introduction, the effects of stock market liquidity on SEO underpricing have not been thoroughly investigated in the literature⁷⁹. To fill the gap in the literature, we conduct a thorough investigation of the relationship, if any, between liquidity and SEO underpricing. Moreover, in this chapter, we examine the relationship between liquidity and underwriting spread (direct SEO cost) in our sample.

7.1. Liquidity and SEO Underpricing

Butler et al. (2005) document an inverse relationship between liquidity of underlying shares and investment banking fees (i.e. the gross spread). As discussed in Chapter Three, both investment banking fees and SEO underpricing belong to flotation costs. The main difference between them is that the former is a type of direct flotation cost and the latter is a type of indirect flotation cost. There is therefore a good chance that an inverse relationship also exists between liquidity of underlying shares and SEO underpricing.

Several studies have already made attempts to incorporate liquidity measures into existing models to explain SEO underpricing. For instance, Corwin (2003) and Kim

⁷⁹ Unless otherwise stated, SEO underpricing refers to the close-to-offer return in this chapter.

and Park (2005) used bid-ask spread as the variable in their analysis⁸⁰. However, interestingly, both interpret bid-ask spread as the proxy of information asymmetry and the results are mixed, probably due to them having used different sets of samples. Kim and Park (2005) did not include bid-ask spread in their multivariate regression but used it as a characteristic indicator to categorise issues. They expected a positive relationship between underpricing and bid-ask spread. Corwin (2003) argued that there is no significant relation between SEO underpricing and bid-ask spread after conducting a set of tests.

Additionally, two working papers, Kalev et al. (2006) and Asem et al. (2009) point to an inverse relation between liquidity of the underlying shares and SEO underpricing for Australian SEOs. In this section, Sample 1 employed in Chapter Six is used to test whether there is a relationship between SEO underpricing and liquidity of the underlying shares.

7.1.1. Hypothesised Inverse Relation between SEO Underpricing and Liquidity

As discussed in Chapter Six, the hypothesis of price pressure or liquidity shocks proposed by Scholes (1972) and Corwin (2003) provides some theoretical support for the inverse relation between liquidity of underlying shares and SEO underpricing. The price pressure can be regarded as either permanent or temporary. In the former case, the impact on share prices is permanent.

⁸⁰ Corwin (2003) defines bid-ask spread as the time-weighted average of percentage quoted spread over 30 days ending 2 days prior to the offer. The data are intraday data collected from Trade and Quote database (TAQ). Kim and Park (2005) use the same definition; however, it seems that their data are collected from CRSP. In CRSP only the closing bid and ask prices are available.

However, Corwin (2003) pointed out that, according to market efficiency theory, the permanent effects should take place on the announcement day rather than the issue day because investors will anticipate the change in the supply and take the expectation into consideration. As a result, the effect of price pressure is more likely to be temporary.

Corwin (2003) further argues that the effects of price pressure would be more significant for shares with relatively inelastic demand. He uses average bid-ask spread to define demand elasticity. If the average bid-ask spread of one stock falls into the highest quartile of bid-ask spread, the share is regarded as a security with inelastic demand (few substitutes). This definition means that the higher the illiquidity of the underlying shares, the higher the demand inelasticity.

As discussed, although the results from Corwin (2003) do not provide support for a relationship between bid-ask spread and demand elasticity, the hypothesised relationship is consistent with Hagerty (1991), who predicted that an increase in the number of substitutes of securities in a market would reduce the liquidity provider's ability to set high spreads. Moulton and Wei (2009) also found a narrower spread and more competitive liquidity provision for crossed listed shares when cross-listing and home market are both open (overlapping trading hours). In sum, the rationale for the hypothesis is that a higher bid-ask spread of stock means fewer substitutes and higher demand inelasticity that leads to higher price pressure and higher SEO underpricing.

In the next section, besides average bid-ask spread, two other measures of liquidity are introduced. The following tests are used to examine whether there is a link between

the liquidity of the underlying securities and indirect flotation costs of equity issuance (SEO underpricing). The hypothesised link, however, does not rely on an equilibrium asset pricing model. In other words, the tests in this section do not check the effects of liquidity on required return.

Empirical tests investigating the effects of liquidity on required return need to check 1) whether liquidity is priced; 2) that the asset pricing model used is correct. Because the tests in this chapter are not based on an equilibrium asset pricing model, the results obtained from the tests do not rely on the assumption that expected return, risk factors, and factor loadings are properly loaded.

7.1.2. Measures of Liquidity

According to data availability, three kinds of liquidity measure are selected for the tests. These measures are relative bid-ask spread, turnover and an illiquidity measure developed by Amihud (2002). Empirical studies prove that all of these measures represent the liquidity/illiquidity of the underlying shares.

Relative Bid-ask Spread is used by many studies in asset pricing (e.g. Amihud and Mendelson, 1986) . It is calculated as quoted average bid-ask spread over the 30 trading days ending two days prior to the offer. Due to the inaccessibility of TAQ data, the bid and ask prices are collected from CRSP⁸¹.

⁸¹ This measure is also adopted by Kim and Park (2005).

$$AvgpSprd_{j,T} = \frac{1}{30} \sum_{t=T-32}^{30} \frac{Ask_{j,t} - Bid_{j,t}}{(Ask_{j,t} + Bid_{j,t})/2}$$

where $AvgpSprd_{j,T}$ represents the quoted average bid-ask spread, T is the issue date and $Ask_{j,t}$ and $Bid_{j,t}$ are the closing ask and bid prices.

Turnover is defined as the number of shares traded divided by the number of shares outstanding for that stock. This definition is also widely used in studies of asset pricing (e.g. Datar et al., 1998). However, one concern about constructing the trading volume should be mentioned. Butler et al. (2005) noticed that in dealer markets (such as NASDAQ) trades are often immediately turned around by the market maker, thereby causing double counting of trading volume. In order to compare the volume with that in auction markets (such as NYSE, Amex), trading volume in NASDAQ is divided by two. In this section, *Turnover* is calculated as the average turnover 120 trading days (approximately six months) prior to the issue. Both the volume and the number of shares outstanding are collected from CRSP on a daily basis.

$$Turnover_T = \frac{1}{120} \sum_{t=T-120}^{120} \frac{Adjusted\ Volume_t}{Outstanding\ shares_t}$$

ILLIQ is the third measure in this section and is an illiquidity measure proposed by Amihud (2002). A lot of fine measures of liquidity/illiquidity required for the calculation of microstructure data on transactions and quotes that are currently not available for this PhD study. In order to mitigate this data problem, the illiquidity measure proposed by Amihud (2002) is introduced. This measure can be regarded as a

supplement to the above two measures. The advantage of the measure is the low requirement for trading data. It does not require intra-daily transaction data and it is calculated from daily data on returns and volume that are readily available in CRSP.

The illiquidity is defined as the daily absolute return divided by the trading volume in dollars on that day, $|R_{iyd}|/VOLD_{iyd}$. $|R_{iyd}|$ is the absolute value of return on stock i on day d of year y and $VOLD_{iyd}$ is the respective daily volume in dollars. This ratio reflects the absolute percentage change in price per dollar of daily trading volume, or the daily price impact of the order flow. Amihud (2002) suggests that this ratio follows the concept of illiquidity that refers to the response of price to order proposed by Kyle (1985) and the measure of thinness (Silber, 1975), defined as the ratio of absolute price change to absolute excess demand for trading. For each share i the annual average

$$ILLIQ_{iy} = 1/D_{iy} \sum_{t=1}^{D_{iy}} |R_{iyd}|/VOLD_{iyd}$$

where D_{iy} is the number of days for which data are available for stock i in year y . In this study, i is set as the day prior to the issue⁸² and D_{iy} is set as at least 180 as the number of trading days per year⁸³. The return is here defined as the daily return including dividend provided by CRSP. As discussed earlier, for NASDAQ issues, the daily volume is divided by two to make it comparable to that of exchange issues.

⁸² In Amihud (2002) i is set as the last trading day of the year. In this study, it is set as the day prior to the issue because there is evidence that the issuance itself will change the liquidity of shares.

⁸³ In Amihud 250 trading days are used, but because some issuers do not have data for 250 trading days prior to the issue, we relax this constraint to at least 180 days in order to obtain more observations.

Amihud (2002) found that the average illiquidity varies considerably over time. To solve this problem, $ILLIQ_{iy}$ is replaced by its mean-adjusted value

$$ILLIQMA_{iy} = ILLIQ_{iy} / AILLIQ_y$$

where $ILLIQMA_{iy}$ is the mean adjusted illiquidity and $ILLIQ_{iy}$ is the illiquidity from the previous formula. $AILLIQ_y$ is defined as:

$$AILLIQ_y = 1/N_y \sum_{t=1}^{N_y} ILLIQ_{iy}$$

where N_y is defined as the total number of issue in year y ⁸⁴.

Table 7-1 Underpricing by liquidity

	Quartile 1 (Lowest)	Quartile 2	Quartile 3	Quartile 4 (Highest)
Relative Bid-Ask Spread Quartile	3.30%	3.00%	2.31%	3.78%
Turnover Quartile	2.77%	2.69%	2.79%	3.36%
ILLIQMA Quartile	2.03%	2.45%	3.05%	4.04%
Bid-ask spread is the average relative bid-ask spread over 30 trading days ending two days prior to the issue. Turnover is the average turnover 120 trading days (approximately six months) prior to the issue. ILLIQMA is the measure proposed by Amihud (2002). There are 4659, 5220, 4551 observations for relative bid-ask spread, turnover and ILLIQMA respectively.				

⁸⁴ This definition is slightly different from Amihud (2002) in that N_y is the number of stocks in the whole sample satisfying the required conditions. However, in an SEO study, this is difficult to replicate due to the much larger sample size. Therefore, a modified definition is used instead of the original.

7.1.3. Empirical Test Results of Liquidity Measures

Table 7-1 lists mean underpricing for quartiles of seasoned offers ranked according to three liquidity variables. Two of them, relative bid-ask spread and turnover, show no trend in SEO underpricing. The results of relative bid-Ask Spread even suggest a U shape for SEO underpricing, which has no theoretical support. Additionally, the descriptive statistics of three liquidity measures are listed in Table 7-2⁸⁵. A first glance at the statistics also suggests no apparent evidence to support the hypothesis that the liquidity of the underlying shares and the SEO underpricing are negatively related.

Table 7-2 Descriptive statistics of three liquidity measures by subperiods

Period	Mean of Relative Bid-ask Spread	No. of Obs.	Mean of Turnover(10^{-3})	No. of Obs.	Mean of ILLIQMA	No. of Obs.
1 (1987-1995)	0.0284	1,461	3.7616	1,500	1.1873	1,260
2 (1996-2001)	0.0166	1,604	5.3230	1,658	0.9231	1,347
3 (2002-2009)	0.0039	1,588	8.0685	1,599	0.7102	1,505
p-value (2)-(1)	1.0000		0.0000		0.9979	
p-value (3)-(2)	1.0000		0.0000		0.9938	
p-value (3)-(1)	1.0000		0.0000		0.9973	
Bid-ask spread is the average relative bid-ask spread over 30 trading days ending two days prior to the issue. Turnover is the average turnover 120 trading days (approximately six months) prior to the issue. ILLIQMA is the measure proposed by Amihud (2002). There are 4659, 5220, 4551 observations for relative bid-ask spread, turnover and ILLIQMA respectively. P-values for difference within subsample means are from standard t-tests.						

⁸⁵ The number of observations for ILLIQMA is fewer than for the other two measures because of missing values in CRSP.

All three measures even show an increase of liquidity of the sample over the three periods. This trend is to some extent consistent with the increase in SEO underpricing over time as discussed in Chapter Four. All of this suggests that there is little evidence to prove the hypothesised inverse relationship between liquidity of underlying shares and SEO underpricing.

As for multivariate tests, the OLS model used in this section is the base model proposed in Chapter Six.

$$\begin{aligned}
 \text{Underpricing} = & \beta_0 + \beta_1 \text{MarketCap} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} \\
 & + \beta_6 \text{CLUSTER} + \beta_7 \text{CloseBidDiffNY} + \beta_8 \text{CloseBidDiffNas} \\
 & + \beta_9 \text{NASDAQDummy} + \beta_{10} \text{Underwriter} + \beta_{11} \text{Toptier} + \beta_{12} \text{Reloffersize} \\
 & + \beta_{13} \text{Bid} - \text{ask spread} + \beta_{14} \text{Turnover} + \beta_{15} \text{ILLIQMA}
 \end{aligned}$$

where liquidity refers to the liquidity measures discussed above and all other variables have been discussed previously. The regression results in Table 7-3 show that there is a significantly positive relationship between liquidity of underlying shares and SEO underpricing. The coefficient of *Bid-ask spread* is -0.13 at a statistically significant level. The coefficient of *Turnover* also shows that there is a positive relationship between liquidity and SEO underpricing. In the 7.1.1, the hypothesis predicts an inverse relationship between liquidity and SEO underpricing, the empirical results, however, indicate a reversed relationship. The results can possibly be explained by either 1) either the transaction cost saving hypothesis or 2) that there is no relation between liquidity and SEO underpricing.

Table 7-3 Regression results for SEO underpricing (with liquidity variables)

	Model 1	Model 2	Model 3
Bid-ask spread	-0.1604*** (-3.27)		
Turnover		0.3212*** (3.38)	
ILLIQMA			-0.0000 (-0.09)
Volatility	0.1812*** (7.73)	0.1438*** (5.72)	0.1745*** (6.77)
MarketCap	0.0010 (1.58)	0.0012* (1.94)	0.0012** (1.96)
CARPos	0.0673*** (7.01)	0.0629*** (6.59)	0.0707*** (6.64)
CARNeg	-0.0037 (-0.40)	-0.0026 (-0.29)	-0.0051 (-0.51)
LnPrice	-0.0155*** (-15.60)	-0.0153*** (-15.68)	-0.0151*** (-14.65)
CLUSTER	0.0112*** (11.72)	0.0113*** (11.95)	0.0113*** (10.95)
CloseBidDiffNY	0.8043*** (5.60)	0.6959*** (5.49)	0.7357*** (5.58)
CloseBidDiffNas	0.7845*** (19.11)	0.7274*** (20.09)	0.7569*** (17.30)
NASDAQDummy	0.0053*** (3.56)	0.0062*** (4.32)	0.0060*** (4.01)
Underwriter	-0.0029** (-2.23)	-0.0027** (-2.12)	-0.0026* (-1.85)
Toptier	-0.0019 (-1.62)	-0.0019* (-1.66)	-0.0020 (-1.60)
Reloffersize	0.0042 (1.32)	0.0027 (0.85)	0.0048 (1.34)
Constant	0.0129 (1.08)	0.0050 (0.45)	-0.0004 (-0.03)
Year Dummy	Yes	Yes	Yes
N	4650	4754	4110
Adjusted R ²	0.3077	0.3092	0.3195
<p>Underpricing is defined as $((P-OP)/P)*100$, where P is the prior offer closing price and OP is the offer price. Bid-ask spread is the average relative bid-ask spread over 30 trading days ending two days prior to the issue. Turnover is the average turnover 120 trading days (approximately six months) prior to the issue. ILLIQMA is a measure proposed by Amihud (2002). Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. MarketCap is the logged pre-issue market capitalization, measured as the price multiplied by the total number of shares outstanding at the market close before the offer. CARPos (CARNeg) is defined as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is negative (positive), where market return is defined as the return on the CRSP value weighted index. LnPrice is the logarithm of closing price prior to the offer. CLUSTER is a Dummy equal to one if the offer price is set at integer. CloseBidDiffNYSE (CloseBidDiffNas) is Closing transaction price-closing bid quote/closing transaction price and is zero if the issuer is list on NASDAQ (NYSE). NASDAQDummy is a dummy variable equal to one if the issuer is list on NASDAQ and zero otherwise. Toptier is a dummy equal to one if the SEO underwriter (book manager) has an analyst group ranked among the top 10 groups selected by Institutional investor each October of the prior calendar year and zero otherwise. Underwriter is a dummy equal to one if the book manager of the syndicate has a reputation rate more than 8 in the ranking proposed by Ritter http://bear.warrington.ufl.edu/ritter/ipodata.htm and zero otherwise. Reloffersize is the ratio between the shares offered to the outstanding shares prior to the offer. Expected proceeds are defined as the production of closing price prior to the offer and shares offered. The value of t statistics is in brackets. ***, **, and * represent 1% 5% and 10% significance, respectively.</p>			

7.1.4. Discussions about the Relation between Liquidity and SEO Underpricing

Regarding the significantly negative relationship between illiquidity and SEO underpricing, one possible explanation is the transaction cost savings hypothesis proposed by Loderer et al. (1991). In an SEO transaction, investors do not need to pay commissions when buying from the underwriters, thus the one way transaction cost is saved for the investors. The underwriters can therefore set offer prices slightly above the preoffer price by the amount of the saved transaction costs.

Regarding the regression result, the decrease in the bid-ask spread represents a decrease in transaction costs. This decline in the transaction costs would constrain the underwriters' ability to set the offer price higher than the preoffer price. As a result, the coefficients of bid-ask spread could be negative. This hypothesis seems to be able to explain the negative coefficient of the bid-ask spread in the regressions. However, there are two doubts related to this explanation.

Firstly, if the increase in SEO underpricing is caused by the decrease of transaction costs, this scenario suggests that there should be some factors that caused the SEO underpricing to be high at the beginning. The SEO underpricing is kept low by the saving of one-way transaction costs in the issue. However, as discussed in Chapter Six, there is no evidence that the above scenario is the case. Indeed, empirical results suggest that in the early 1990s, the common practice for NASDAQ issues was to set the offer price at the closing bid prior to the offer. The prominence of such a practice clearly indicates that it is highly unlikely that some factors caused the increase in SEO underpricing in the first place.

The second doubt is that the regression results in Table 7-3 suggest that SEO underpricing is positively associated with liquidity when measured by all three kinds of variable. Therefore, even assuming that the transaction cost savings hypothesis is reasonable, the hypothesis is still unable to explain the results for two other variables; the empirical results further confirm the doubts regarding the transaction cost savings hypothesis.

The above discussions suggest that the transaction cost saving hypothesis cannot explain the empirical results persuasively, thus another explanation is that there is indeed no relationship between SEO underpricing and liquidity of underlying shares. The empirical results only reflect the changed sample composite: with more and more firms with high market capitalisation issuing seasoned equity, the average liquidity of the sample consequently decreases.

In other words, when an underwriter decides the offer price, liquidity of the underlying shares might not be a consideration. In sum, empirical evidence and discussions in this session suggest that 1) the average liquidity level of the shares in the sample is increasing over time; 2) the hypothesised inverse relationship between SEO underpricing and liquidity of underlying shares has little empirical support; 3) liquidity of the underlying shares may not be a consideration or determinant of SEO underpricing. The positive relation between SEO underpricing and liquidity is likely to be a reflection of the changed sample composite.

7.2. Liquidity and SEO Gross Spread

In the previous section, we concluded that liquidity is probably not a consideration or determinant for SEO underpricing. In the literature, the liquidity of underlying shares is shown to have negative effects on SEO investment banking fees (gross spread). In this section, this relation is tested again using our sample.

7.2.1. Model Specification

The model used to estimate SEO gross spread is based on Butler et al. (2005). However, constrained by data availability, we modify the model to make it more suitable for our dataset. Sample 1 in Chapter Four is used to test the model. The model is presented as follows. Control variables include volatility, price level and the size of the firm, expected proceeds, underwriter reputation dummy and multiple-book runner dummy. Liquidity variables are the three liquidity variables introduced in 7.1.

Volatility is defined as the standard deviation of daily close-to-close returns over 30 trading days ending 11 days prior to the offer. Many studies use volatility as a proxy for risk or value uncertainty (e.g. Jeon and Ligon, 2011; Lee and Masulis, 2009). High volatility means more risks for the underwriters. Therefore, consistent with the literature, we expect a positive relationship between volatility and gross spread.

Size of the Issuer is used as the proxy for information asymmetry and is defined as log of market capitalisation. As suggested by many studies (e.g. Corwin, 2003; Lee and Masulis, 2009), firms with high capitalisation are more likely to draw attention from stock analysts, business news services, institutional investors and other market

participants. Therefore, there would be more information available about larger firms and less information asymmetry. Size of the issuer is expected to be negatively related to gross spread.

Proceeds are defined as the natural logarithm of the number of issues multiplied by the prior closing price. This variable is used to describe the economy of scale effect in gross spread that was first documented by Smith (1977). The economy of scale has been confirmed by many studies such as Eckbo and Masulis (1992) and Hansen (2001). A negative relationship is expected between gross spread and proceeds.

Price Level is defined as the natural logarithm of the closing price prior to the issue. Compared with other control variables, this variable is less frequently utilised by studies in investment banking fees. Butler et al. (2005) suggest that institutional investors tend to shun low-priced stocks, making it more difficult for investment banks to place low-priced issues. Thus we expect a negative relationship between price level and gross spread.

NASDAQ Dummy is a dummy variable equal to one if the shares of the firm are listed on NASDAQ. As discussed in Chapter Six, firms listed on NASDAQ are often smaller and therefore riskier than those listed on NYSE. Corwin and Harris (2001) point out the possible reason that these firms can avoid expected delisting costs by choosing NASDAQ. Because NASDAQ firms are smaller and riskier, their shareholder base would be smaller, leading to more efforts to place the issues for underwriters. Therefore, NASDAQ Dummy and gross spread are expected to be positively related.

Underwriter Reputation Dummy is a dummy variable equal to one if the book managers of the issue have a ranking of more than 8.0. The ranking is provided by Ritter on his website <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. Puri (1999) argues that investment banks with higher reputations can charge higher fees because the underwriting market is oligopolistic. Butler et al. (2005) also suggest a positive relationship between underwriter reputation and the underwriting fees because prestigious banks work harder. However, Li and Masulis (2007) suggest a negative relationship between underwriter reputation and the underwriting fees by arguing that higher ranked underwriters have lower expected due diligence costs and, thus, they are able to charge lower costs in a competitive market.

Multiple-book runner Dummy is a dummy variable equal to one if the issue is underwritten by multiple book managers. Butler et al. (2005) included this variable because they argue that multiple book managers may be more efficient in forming syndicates and selling shares than a single book manager. Therefore, a negative relationship is expected between this variable and gross spread. Jeon and Ligon (2011) also included this dummy in their study and but found a positive relationship between underwriting fees and this dummy variable.

7.2.2. Regression Results for Gross Spread

The regression results are presented in Table 7-4. Several findings can be drawn from the regression results. A first glance suggests that the explanation power of these models is impressive. All of them have an adjusted R^2 of around 0.60. These numbers

are close to the adjusted R^2 in Butler et al. (2005). Moreover, three findings in particular are discussed as follows.

Table 7-4 OLS regression results for gross spread

Model	1	2	3	4
Bid-ask spread		2.9724*** (3.08)		
turnover			0.0194 (1.41)	
ILLIQMA				0.0079 (1.21)
Volatility	7.6119*** (13.97)	7.0713*** (12.47)	7.3098*** (12.52)	7.4626*** (11.90)
MarketCap	-0.6124*** (-35.71)	-0.5834*** (-29.96)	-0.6134*** (-35.70)	-0.6314*** (-33.06)
LnProceeds	0.0477** (2.28)	0.0214 (0.96)	0.0432** (2.05)	0.0641*** (2.81)
LnPrice	-0.1122*** (-4.94)	-0.0589** (-2.48)	-0.1102*** (-4.83)	-0.1074*** (-4.35)
NASDAQDummy	0.4977*** (16.92)	0.4604*** (13.46)	0.4910*** (16.41)	0.4916*** (15.63)
Underwriter	-0.1067*** (-3.63)	-0.0930*** (-3.08)	-0.1082*** (-3.67)	-0.0865*** (-2.64)
MultiBook	0.3844*** (11.82)	0.3816*** (11.12)	0.3800*** (11.59)	0.4109*** (11.72)
Constant	15.9963*** (66.61)	15.7333*** (50.38)	16.0894*** (64.78)	16.0412*** (59.30)
N	5156	4593	5153	4478
Adjusted R^2	0.6160	0.5966	0.6159	0.6125
<p>GrossSpread is defined as a percentage of the issue proceeds. Bid-ask spread is the average relative bid-ask spread over 30 trading days ending two days prior to the issue. Turnover is the average turnover 120 trading days (approximately six months) prior to the issue. ILLIQMA is the measure proposed by Amihud (2002). Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. MarketCap is the logarithm of the market value of the firm defined as the production of prior closing price and outstanding shares. LnPrice is the logarithm of closing price prior to the offer. NASDAQDummy is a dummy variable equal to one if the issuer is list on Nasdaq. LnProceeds is the logarithm of the expected proceeds that are defined as the production of closing price prior to the offer and shares offered. Underwriter is a dummy equal to one if the book manager of the syndicate has a reputation rate more than 8 in the ranking proposed by Ritter http://bear.warrington.ufl.edu/ritter/ipodata.htm, zero otherwise. MultiBook is a dummy equal to one if there are more than one book manager in the syndicate. The value of t statistics is in brackets. ***, **, and * represent 1% 5% and 10% significance, respectively.</p>				

First, the results confirm that liquidity is an important concern in deciding investment banking fees (gross spread). Two of the liquidity measures have the predicted relation with gross spread; the coefficient of *Turnover* is not statistically significant and has the wrong sign. These results can be explained by the rationale that shares with high liquidity are easier for underwriters to place than those with low liquidity (Butler et al., 2005). Thus, underwriters charge higher gross spread for issues of low liquidity shares. In our study, despite the difference in sample settings [e.g. the length of the sample period (1987-2009) is much longer than that (1993-2000) in Butler et al. (2005)], our results are still consistent with Butler et al. (2005).

Second, we confirm the effects of some factors on SEO gross spread indicated by Butler et al. (2005). Issues with higher risk shares (high volatility) tend to be charged at higher gross spread. And bigger firms (with higher capitalization) that have less information asymmetry enjoy lower gross spread. For NASDAQ issues, they are charged at higher gross spread due to their characteristics. The significant negative coefficients of *LnPrice* confirm that it is more difficult to place low price issues for underwriters.

Finally, we find some results of the regression inconsistent to those claimed by Butler et al. (2005). The *MultiBook* Dummy shows positive effects on gross spread in all models, which is consistent with Jeon and Ligon (2011). This positive relationship suggests that multiple book runners do not necessarily mean high efficiency but might lead to high cost. The negative coefficients of *Underwriter* dummy variables indicate that the high reputation banks have lower expected due diligence and thus can afford to reduce the gross spread. This significantly negative relationship also implies that

the underwriting market is still a competitive market. The fact that the signs of the coefficients of *LnProceeds* are positive is inconsistent to the hypothesis of economy scale suggested by many studies. However, this relation can still be explained by the hypothesis of U-shape of economy scale proposed by Altinkiliç and Hansen (2000).

CHAPTER 8: ROBUSTNESS TESTS

The robustness tests in this chapter deal mainly with alternative specifications. Specifically, we check the sensitivity to the choice of control variables of the results reported in Chapter Six. For instance, due to the data limitations, some observations without closing bid quotes were removed from the multivariate tests in Chapter Six. It is therefore necessary to re-estimate the regressions with alternative specifications.

8.1. Liquidity Shocks caused by Market Conditions

The variable *CloseBidDiffNas* represents the practice of setting offer prices at the closing bid quote for NASDAQ issues. As mentioned in Chapters Four and Six, there are a number of missing bid and ask quotes in CRSP. Therefore, including the variable *CloseBidDiffNas* means some observations are excluded from the regressions. In this section, the regression analysis is conducted without *CloseBidDiffNas*. Moreover, we also remove the independent variable *Toptier* because the variable is not often employed in SEO underpricing studies. After excluding these variables, we re-estimate the regressions using model (8.1) and check whether our previous results still hold.

$$\begin{aligned} \text{Underpricing} = & \beta_0 + \beta_1 \text{MarketCap} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} + \\ & \beta_6 \text{CLUSTER} + \beta_7 \text{NASDAQDummy} + \beta_8 \text{Underwriter} + \beta_9 \text{Reloffersize} + \\ & \beta_{10} \text{RAProceedsSEO90} + \beta_{11} \text{Market250} + \beta_{12} \text{MarketVolatility}. \end{aligned} \quad (8.1)$$

Table 8-1 OLS regression results for SEO underpricing

	Model 1	Model 2	Model 3	Model 4	Model 5
MarketCap	0.0006 (1.11)	0.0006 (1.15)	0.0006 (1.09)	0.0006 (1.09)	0.0006 (1.15)
Volatility	0.2008*** (8.83)	0.1991*** (8.74)	0.1989*** (8.67)	0.1922*** (8.40)	0.1938*** (8.44)
CARPos	0.0666*** (6.96)	0.0666*** (6.96)	0.0664*** (6.94)	0.0670*** (7.00)	0.0674*** (7.04)
CARNeg	0.0111 (1.25)	0.0122 (1.36)	0.0113 (1.26)	0.0131 (1.47)	0.0139 (1.54)
LnPrice	-0.0163*** (-17.46)	-0.0163*** (-17.47)	-0.0163*** (-17.45)	-0.0162*** (-17.41)	-0.0162*** (-17.42)
CLUSTER	0.0113*** (12.27)	0.0113*** (12.24)	0.0113*** (12.25)	0.0113*** (12.21)	0.0113*** (12.21)
NASDAQDummy	0.0054*** (4.76)	0.0055*** (4.82)	0.0055*** (4.80)	0.0058*** (5.04)	0.0058*** (5.01)
Underwriter	-0.0061*** (-5.44)	-0.0060*** (-5.42)	-0.0060*** (-5.42)	-0.0059*** (-5.32)	-0.0059*** (-5.32)
Reloffersize	0.0133*** (4.70)	0.0134*** (4.74)	0.0133*** (4.72)	0.0137*** (4.84)	0.0137*** (4.84)
RAProceeds90SEO		0.0008 (1.13)			0.0006 (0.71)
Market250			-0.0062 (-0.68)		0.0129 (1.17)
MarketVolatility				0.4427*** (3.20)	0.5121*** (3.23)
Constant	0.0329*** (3.37)	0.0314*** (3.19)	0.0331*** (3.39)	0.0308*** (3.15)	0.0291*** (2.93)
Year Dummy	Yes	Yes	Yes	Yes	Yes
N	5339	5339	5339	5339	5339
Adjusted R ²	0.2632	0.2632	0.2631	0.2644	0.2644

Underpricing is defined as $((P-OP)/P)*100$, where P is the prior offer closing price and OP is the offer price. Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. MarketCap is the logged pre-issue market capitalization, measured as the price multiplied by the total number of shares outstanding at the market close before the offer. CARPos (CARNeg) is defined as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is negative (positive), where market return is defined as the return on the CRSP value weighted index. CLUSTER is a Dummy equal to one if the offer price is set at integer. NASDAQDummy is a dummy variable equal to one if the issuer is list on NASDAQ. Underwriter is a dummy equals one if one of the lead underwriters has the reputation rank equal to or greater than 8 and zero otherwise. The ranking is made by Ritter and available on <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. Reloffersize is the ratio between the shares offered to the outstanding shares prior to the offer. RAProceeds90SEO is the ratio of aggregate SEO proceeds over the 90 trading days ending 1 day before the offer to the overall market capitalization prior to the offer day. MarketVolatility is the standard deviations of daily returns, computed using equal-weighted portfolios of all firms listed on NYSE/AMEX/NASDAQ/ARCA for the 21-trading-day returns ending one day before the offer day. Market250 the proxy of liquidity shocks caused by market decline, $Market250 = MarketReturn250 * D_{market}$ where MarketReturn250 is the return on CRSP index over the prior 250 trading days and D_{market} equals one if MarketReturn250>0 and zero otherwise. The value of t statistics is in brackets. ***, **, and * represent 1% 5% and 10% significance, respectively.

In Table 8-1, regression results with alternative specifications are presented. The size of the sample increases to 5339 since many issues without closing bid quotes in CRSP are included in the regression analysis. The results are similar to those in Table 6-6. Specifically, the *MarketVolatility* coefficient has the predicted sign and is statistically significant at the 1% level. This result indicates that market volatility is positively associated with SEO underpricing after controlling for other factors. Moreover, *Volatility*, *CARPos*, *LnPrice*, *CLUSTER*, *NASDAQDummy*, *Underwriter* and *Reloffersize* are of the predicted sign and are statistically significant at the 1% level.

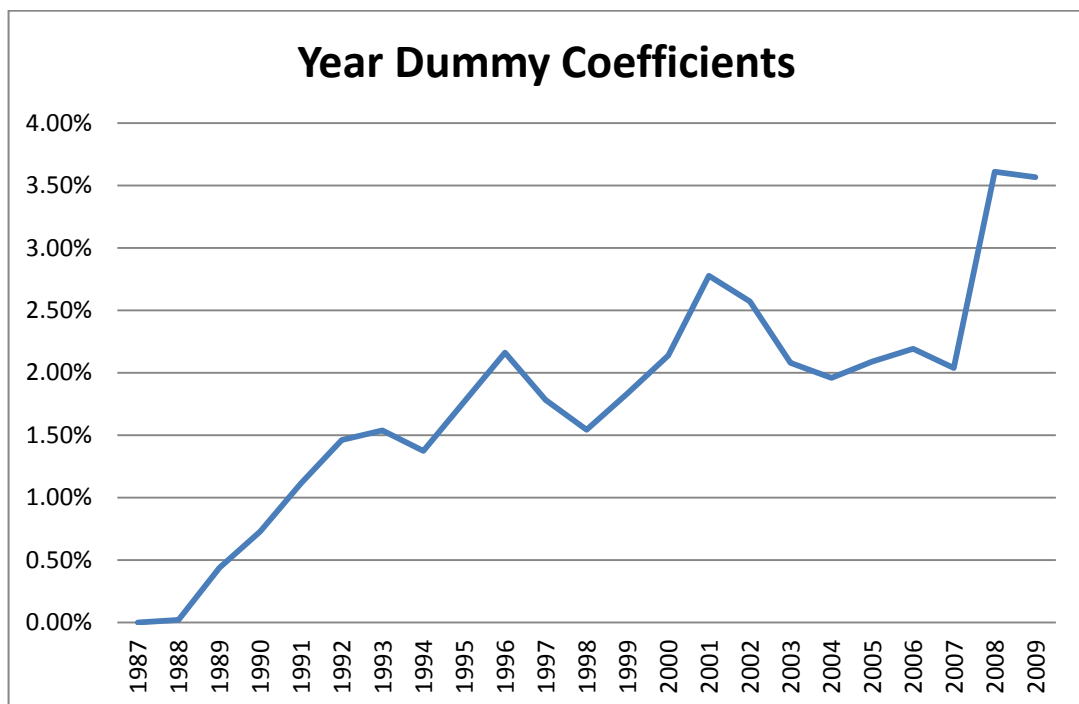


Figure 8-1 Year dummy coefficients in regression of underpricing on control variables

8.2. The Behaviour of SEO Underpricing over Time

In this section, we examine the behaviour of SEO underpricing over time by the estimation method proposed by Chambers and Dimson (2009). In Figure 8-1, the dummy year coefficients are estimated by model (8.1). In the regression, all explanatory variables except for the year dummies are demeaned. The figure shows an upward shift in annual SEO dummies, and if we divide the sample period into two subperiods 1987-1997 and 1998-2009, the number-weighted means of year dummy coefficients are 1.41% and 2.36% respectively: an increase of 0.95%.

We next divide the sample into two subsamples. The first sample only includes SEOs that are priced at next lower or other lower integer prices. The second sample includes the remaining SEOs. For each sample, the coefficients of year dummy are estimated by model (8.2). The dummy year coefficients for the first sample are graphed in Figure 8-2. Again, we divide the sample periods into two subperiods 1987-1997 and 1998-2009. The number-weighted mean of dummy year coefficients for 1987-1997 is 1.39%. The number increases to 2.41% for 1998-2009.

$$\begin{aligned} \text{Underpricing} = & \beta_0 + \beta_1 \text{MarketCap} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} + \\ & \beta_6 \text{NASDAQDummy} + \beta_7 \text{Underwriter} + \beta_8 \text{Reloffersize} + \beta_9 \text{RAProceedsSEO90} + \\ & \beta_{10} \text{Market250} + \beta_{11} \text{MarketVolatility}. \end{aligned} \quad (8.2)$$

Figure 8-3 shows the pattern of dummy year coefficients for the second sample. The figure shows an upward shift of annual dummies over time. The number-weighted means of dummy year coefficients for 1987-1997 and 1998-2009 are 1.25% and 2.26% respectively: an increase of 1.01%. The result shows that SEOs that are not priced at

lower integer prices have a similar pattern of underpricing to that of SEOs with lower integer prices, indicating that setting the offer price at lower integers cannot fully explain the upward shift of SEO underpricing over time.

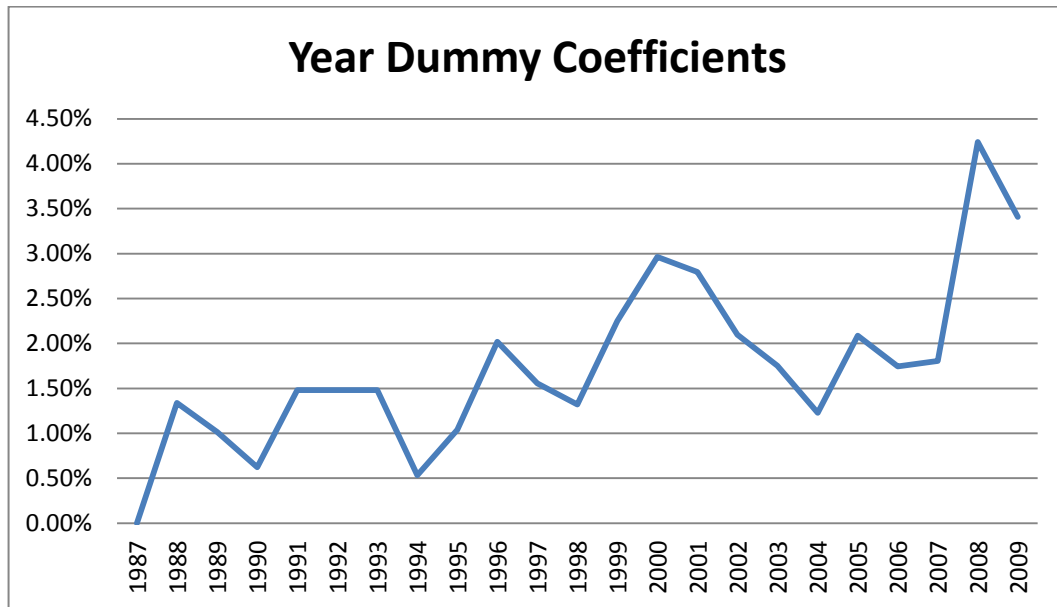


Figure 8-2 Year dummy coefficients for the subsample that only includes SEOs that are priced at lower integer offer prices

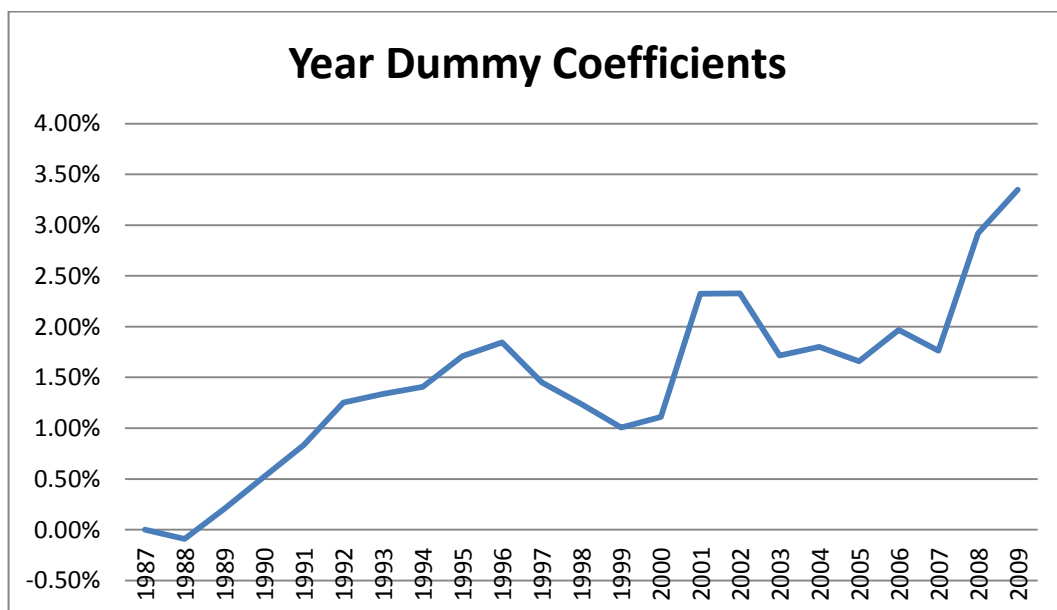


Figure 8-3 Year dummy coefficients for the subsample that only includes SEOs that are not priced at lower integer offer prices

8.3. The Logit Analysis of Setting Offer Price at Lower Integer

We next conduct a logit analysis similar to Table 6-7 but with alternative specifications. The logit model is model (8.3). In Model 1, the dependent variable is OTHER LOWER INTEGER dummy. This binary variable is equal to one if the offer price is set at other lower integers relative to the prior closing price and zero otherwise. For instance, assuming the prior closing price is \$10.7, the dummy is one if the offer price is set at \$9 or lower integers (\$8, 7, etc.).

$$\begin{aligned} (Other)Lower\ Integer = & \beta_0 + \beta_1 MarketCap + \beta_2 Volatility + \beta_3 CARPos + \beta_4 CARNeg + \\ & \beta_5 LnPrice + \beta_6 NASDAQDummy + \beta_7 Underwriter + \beta_8 Reloffersize + \beta_9 RAProceedsSEO90 + \\ & \beta_{10} Market250 + \beta_{11} MarketVolatility + \beta_{12} MTH + \beta_{13} DecimalDummy. \end{aligned} \quad (8.3)$$

In Model 2, the dependent variable for this set is LOWER INTEGER dummy. The variable takes one if the offer price is set at either next lower integer or other lower integers relative to the prior closing price, and zero otherwise. Taking the above example again, the dummy is one if the offer price is set at \$10 or lower integers (\$9, 8, etc.)

The results in both models are similar to those in Table 6-7. Specifically, the time variable *MTH* is positively and significantly related to the likelihood of setting the offer price at (other) lower integer after controlling for other factors. The results confirm that the practice of setting offer price at lower integer has become more prevalent over time.

Table 8-2 Logit regression of other lower integer dummy variable/next lower or other lower integer dummy variable

	Model 1	Model 2
MarketCap	-0.1042*** (-3.28)	-0.0686*** (-2.88)
Volatility	8.5379*** (7.63)	5.2122*** (5.57)
CARPos	0.7312 (1.54)	0.0471 (0.12)
CARNeg	-1.3858*** (-3.00)	-1.4090*** (-3.86)
LnPrice	0.7581*** (13.33)	0.2807*** (7.13)
NASDAQDummy	0.2550*** (3.70)	0.2632*** (5.25)
Underwriter	-0.0452 (-0.71)	0.0492 (1.04)
Reloffersize	0.3921** (2.57)	0.3898*** (3.32)
MTH	0.0043*** (5.41)	0.0041*** (7.13)
decimaldummy	-0.3640*** (-3.30)	-0.4296*** (-5.13)
RAProceeds90SEO	0.0391 (1.17)	-0.0019 (-0.08)
Market250	-0.6279 (-1.32)	-0.8294** (-2.27)
MarketVolatility	3.7881 (0.49)	-0.5287 (-0.08)
Constant	-2.7871*** (-5.10)	-1.0202** (-2.47)
N	5339	5339
Pseudo R ²	0.1515	0.0553

In Model 1, the Dependent variable is Other Lower Integer Dummy which is equal to one if the offer price is set at the other lower integers relative to the prior closing price and zero otherwise. For instance, assuming the prior closing price of an issue is \$10.7, the OTHER LOWER INTEGER dummy is one if the offer price is set at \$9 or lower integers (\$8, 7, etc.). Panel B The Dependent variable is Next Lower Integer or Other Lower Integer Dummy which is equal to one if the offer price is set at either the next lower integer or other lower integers relative to the prior closing price and zero otherwise. For instance, assuming the prior closing price of an issue is \$10.7, the Next Lower Integer/OTHER LOWER INTEGER dummy is one if the offer price is set at \$10 or lower integers (\$9, 8, 7, etc.). Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. MarketCap is the logged pre-issue market capitalization, measured as the price multiplied by the total number of shares outstanding at the market close before the offer. CARPos (CARNeg) is defined as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is negative (positive), where market return is defined as the return on the CRSP value weighted index. CLUSTER is a Dummy equal to one if the offer price is set at integer. NASDAQDummy is a dummy variable equal to one if the issuer is list on NASDAQ. Underwriter is a dummy equals one if one of the lead underwriters has the reputation rank equal to or greater than 8 and zero otherwise. The ranking is made by Ritter and available on <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. Reloffersize is the ratio between the shares offered to the outstanding shares prior to the offer. RAProceeds90SEO is the ratio of aggregate SEO proceeds over the 90 trading days ending 1 day before the offer to the overall market capitalization prior to the offer day. MarketVolatility is the standard deviations of daily returns, computed using equal-weighted portfolios of all firms listed on NYSE/AMEX/NASDAQ/ARCA for the 21-trading-day returns ending one day before the offer day. Market250 the proxy of liquidity shocks caused by market decline, $\text{Market250} = \text{MarketReturn250} * D_{\text{market}}$, where MarketReturn250 is the return on CRSP index over the prior 250 trading days and D_{market} equals one if MarketReturn250 > 0 and zero otherwise. White's heteroskedasticity-adjusted z-statistics are in parentheses. ***, **, and * represent 1% 5% and 10% significance, respectively.

CHAPTER 9: CONCLUSION

9.1. Summary

Inspired by: 1) the increase of seasoned equity offering underpricing during the past two decades; 2) some evidence inconsistent with the existing explanations for the increase of SEO underpricing; and 3) the neglect of liquidity, liquidity shocks and market conditions in the existing studies on SEO underpricing, in this PhD thesis, we have included market conditions into the empirical SEO underpricing models and examined the behaviour of SEO underpricing over the sample period from 1987 to 2009.

We hypothesised that certain market conditions could cause liquidity shocks that would consequently increase SEO underpricing. We developed three proxies to represent three scenarios of market conditions, namely aggregate issues with large volume, large market decline, and market volatility. Using a sample of more than 5000 seasoned equity offerings in the US between 1987 and 2009, we found that market volatility was significantly and positively associated with SEO underpricing after controlling for other factors⁸⁶.

In our sample, we documented not only a substantial magnitude of SEO underpricing (including both close-to-offer return and offer-to-close return) but also a statistically

⁸⁶ Unless otherwise stated, the underpricing refers to the close-to-offer return in this thesis.

and economically significant increase in SEO underpricing over time. The average magnitude of underpricing over the sample period was 2.90%⁸⁷, which means that a large amount of money was left on the table by issuers⁸⁸. Moreover, we divided the sample into three sub samples and found that the average SEO underpricing increased from 2.12% in 1987-1995 to 3.01% in 1996-2001, then to 3.75% in 2002-2009. This increase in SEO underpricing is consistent with Altinkilic and Hansen (2003), Corwin (2003), Kim and Shin (2004), Mola and Loughran (2004) and Autore (2011).

To examine the behaviour of SEO underpricing over the long run, we employed the estimation method proposed by Chambers and Dimson (2009). Under this method, all explanatory variables except year dummies are demeaned, then the coefficients of the year dummies are estimated using a regression model. The year dummy coefficients represent the magnitude of SEO underpricing after controlling for changing risk composition, price practice, market conditions and the influence of underwriter reputation and analyst coverage.

We found an upward shift in the annual dummies over our sample period from 1987 to 2009. The number-weighted means of the year dummy coefficients for 1987 to 1997 and 1998 to 2009 were 1.80% and 3.49% respectively: an increase of 1.69%⁸⁹. Then we divided the sample into two subsamples: one only included SEOs that were priced at next lower or other lower integer prices and the other included the remaining SEOs. The patterns of the year dummy coefficients in the two subsamples were similar,

⁸⁷ The underpricing refers to the close-to-offer return.

⁸⁸ In our sample, the average amount of money left on the table by SEO underpricing/discount is \$5.37 million in the equivalent of 2009 US dollars for the period 1987-2009.

⁸⁹ The coefficients of year dummies are weighted by the number of SEOs each year in the sample.

which indicated that setting offer prices at lower integers cannot fully explain the upward shift of annual underpricing dummies.

We hypothesised that the upward shift in the annual dummies over our sample period could be explained by increasing investment banking power. In the literature, a number of studies have claimed that the industry structure of underwriting has transferred from a competitive market to an oligopoly market, and banks use non-price dimensions to gain market power and consequently increase SEO underpricing (e.g. Loughran and Ritter, 2004; Liu and Ritter, 2011). We also found some evidence of increasing investment banking power in our sample. By employing a probit model, we found that the practice of setting offer prices at lower integers has become prevalent over time, all else being equal.

9.2. Future Work

We borrowed the investment banking power hypothesis in the literature to explain the upward shift in the annual underpricing dummies in our sample. Studies in IPO underpricing have found strong evidence that underwriters use analyst coverage as a non-price dimension to gain more market power and consequently underprice IPOs more (e.g. Liu and Ritter, 2011).

However, in our sample, we found no evidence that underwriters use analyst coverage as a non-price dimension to increase SEO underpricing. Specifically, after controlling for other factors, the toptier analyst dummy was insignificantly and negatively related to SEO underpricing over the sample period from 1987 to 2009. This result indicates

that analyst coverage might not be an appropriate proxy of investment banking power in SEO studies, and other non-price dimensions might be employed by underwriters to remain their oligopoly status. Therefore, future research could focus on other non-price dimensions and examine whether some of them could serve as proxies of investment banking power in SEO underpricing.

Moreover, by using the estimation method proposed by Chambers and Dimson (2009), we could examine the behaviour of IPO underpricing over time in the US market. If we can observe a similar pattern in the annual IPO underpricing dummies as that in SEOs, we can view the finding as indirect evidence of investment banking power.

REFERENCES

- Acharya, V. V. & Pedersen, L. H. 2005. Asset pricing with liquidity risk. *Journal of Financial Economics*, 77, 375-410.
- Allen, F. & Faulhaber, G. R. 1989. Signalling by underpricing in the IPO market. *Journal of Financial Economics*, 23, 303-323.
- Alti, A. & Sulaeman, J. 2012. When do high stock returns trigger equity issues? *Journal of Financial Economics*, 103, 61-87.
- Altinkilic, I. O. & Hansen, R. S. 2003. Discounting and underpricing in seasoned equity offers. *Journal of Financial Economics*, 69, 285-323.
- Altinkiliç, O. & Hansen, R. S. 2000. Are there economies of scale in underwriting fees? Evidence of rising external financing costs. *Review of Financial Studies*, 13, 191.
- Amihud, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5, 31-56.
- Amihud, Y. & Mendelson, H. 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17, 223-249.
- Armitage, S. 2010. Block Buying and Choice of Issue Method in UK Seasoned Equity Offers. *Journal of Business Finance & Accounting*, 37, 422-448.
- Asem, E., Chung, J. & Tian, G. 2009. Liquidity, Investor Sentiment and Price Discount of SEOs in Australia. *Working paper*, University of Lethbridge, Australia.
- Asquith, P. & Mullins, D. W. 1986. Equity issues and offering dilution. *Journal of Financial Economics*, 15, 61-89.
- Autore, D. M. 2011. Does Rule 10b-21 increase SEO discounting? *Journal of Financial Intermediation*, 20, 231-247.
- Baker, M. & Wurgler, J. 2002. Market Timing and Capital Structure. *Journal of Finance*, 57, 1-32.
- Barclay, M. J. & Litzenberger, R. H. 1988. ANNOUNCEMENT EFFECTS OF NEW EQUITY ISSUES AND THE USE OF INTRADAY PRICE DATA. *Journal of Financial Economics*, 21, 71-99.
- Barry, C. B., Muscarella, C. J., Peavy Iii, J. W. & Vetsuypens, M. R. 1990. The role of venture capital in the creation of public companies: Evidence from the going-public process. *Journal of Financial Economics*, 27, 447-471.
- Barry, C. B., Muscarella, C. J. & Vetsuypens, M. R. 1991. Underwriter warrants, underwriter compensation, and the costs of going public. *Journal of Financial Economics*, 29, 113-135.
- Bayless, M. & Chaplinsky, S. 1996. Is There a Window of Opportunity for Seasoned Equity Issuance? *Journal of Finance*, 51, 253-278.
- Beatty, R. P. & Welch, I. 1996. ISSUER EXPENSES AND LEGAL LIABILITY IN INITIAL PUBLIC OFFERINGS. *Journal of Law & Economics*, 39, 545-602.
- Benveniste, L. M. & Spindt, P. A. 1989. How investment bankers determine the offer price and allocation of new issues. *Journal of Financial Economics*, 24, 343-361.
- Bernardo, A. E. & Welch, I. 2004. Liquidity and Financial Market Runs. *Quarterly Journal of Economics*, 119, 135-158.

- Booth, J. R. & Smith, R. L. 1986. Capital raising, underwriting and the certification hypothesis. *Journal of Financial Economics*, 15, 261-281.
- Bortolotti, B., Megginson, W. & Smart, S. B. 2008. The Rise of Accelerated Seasoned Equity Underwritings. *Journal of Applied Corporate Finance*, 20, 35-57.
- Bowen, R. M., Xia, C. & Qiang, C. 2008. Analyst Coverage and the Cost of Raising Equity Capital: Evidence from Underpricing of Seasoned Equity Offerings. *Contemporary Accounting Research*, 25, 657-699.
- Box, G. E. P., Jenkins, G. M. & Reinsel, G. C. 2008. *Time series analysis : forecasting and control / George E.P. Box, Gwilym M. Jenkins, Gregory C. Reinsel*, John Wiley.
- Bradley, D. J., Cooney Jr, J. W., Jordan, B. D. & Singh, A. K. 2004. Negotiation and the IPO Offer Price: A Comparison of Integer vs. Non-Integer IPOs. *Journal of Financial & Quantitative Analysis*, 39, 517-540.
- Brav, A. 2000. Inference in Long-Horizon Event Studies: A Bayesian Approach with Application to Initial Public Offerings. *The Journal of Finance*, 55, 1979-2016.
- Brav, A., Geczy, C. & Gompers, P. A. 2000. Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics*, 56, 209-249.
- Brealey, R. A., Myers, S. C. & Allen, F. 2006. *Corporate Finance*, 8th ed., International ed. Boston, Mass. ; London : , McGraw-Hill Irwin, p371-372, p390, p943.
- Brennan, M. J. & Subrahmanyam, A. 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, 41, 441-464.
- Brunnermeier, M. K. & Pedersen, L. H. 2009. Market Liquidity and Funding Liquidity. *The Review of Financial Studies*, 22, 2201-2238.
- Butler, A. W., Grullon, G. & Weston, J. P. 2005. Stock Market Liquidity and the Cost of Issuing Equity. *Journal of Financial & Quantitative Analysis*, 40, 331-348.
- Carlson, M., Fisher, A. & Giammarino, R. O. N. 2006. Corporate Investment and Asset Price Dynamics: Implications for SEO Event Studies and Long-Run Performance. *Journal of Finance*, 61, 1009-1034.
- Carter, R. & Manaster, S. 1990. Initial Public Offerings and Underwriter Reputation. *Journal of Finance*, 45, 1045-1067.
- Carter, R. B., Dark, F. H. & Singh, A. K. 1998. Underwriter Reputation, Initial Returns, and the Long-Run Performance of IPO Stocks. *Journal of Finance*, 53, 285-311.
- Chacko, G. C., Jurek, J. W. & Stafford, E. 2006. Pricing liquidity, the quantity structure of immediacy prices. *Working paper*, Harvard University. .
- Chacko, G. C., Jurek, J. W. & Stafford, E. 2008. The Price of Immediacy. *Journal of Finance*, 63, 1253-1290.
- Chambers, D. & Dimson, E. 2009. IPO Underpricing over the Very Long Run. *The Journal of Finance*, 64, 1407-1443.
- Chang, X. I. N. & Dasgupta, S. 2009. Target Behavior and Financing: How Conclusive Is the Evidence? *The Journal of Finance*, 64, 1767-1796.
- Chaplinsky, S. & Ramchand, L. 2000. The Impact of Global Equity Offerings. *Journal of Finance*, 55, 2767-2789.
- Chemmanur, T. & Yan, A. 2009. Product market advertising and new equity issues. *Journal of Financial Economics*, 92, 40-65.
- Chemmanur, T. J. 1993. The Pricing of Initial Public Offerings: A Dynamic Model with Information Production. *Journal of Finance*, 48, 285-304.

- Chemmanur, T. J., He, S. & Hu, G. 2009. The role of institutional investors in seasoned equity offerings. *Journal of Financial Economics*, 94, 384-411.
- Chemmanur, T. J. & Jiao, Y. 2011. Institutional Trading, Information Production, and the SEO Discount: A Model of Seasoned Equity Offerings. *Journal of Economics & Management Strategy*, 20, 299-338.
- Chen, H.-C., Fauver, L. & Yang, P.-C. 2009. What do investment banks charge to underwrite American Depositary Receipts? *Journal of Banking & Finance*, 33, 609-618.
- Chen, H.-C. & Ritter, J. R. 2000. The Seven Percent Solution. *Journal of Finance*, 55, 1105-1131.
- Cliff, M. T. & Denis, D. J. 2004. Do Initial Public Offering Firms Purchase Analyst Coverage with Underpricing? *The Journal of Finance*, 59, 2871-2901.
- Corwin, S. A. 2003. The Determinants of Underpricing for Seasoned Equity Offers. *Journal of Finance*, 58, 2249-2279.
- Corwin, S. A. & Harris, J. H. 2001. The Initial Listing Decisions of Firms That Go Public. *Financial Management (Blackwell Publishing Limited)*, 30, 35.
- Corwin, S. A. & Schultz, P. 2005. The Role of IPO Underwriting Syndicates: Pricing, Information Production, and Underwriter Competition. *Journal of Finance*, 60, 443-486.
- Coval, J. & Stafford, E. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86, 479-512.
- Da, Z. & Gao, P. 2010. Clientele Change, Liquidity Shock, and the Return on Financially Distressed Stocks. *Journal of Financial & Quantitative Analysis*, 45, 27-48.
- Datar, V. T., Y. Naik, N. & Radcliffe, R. 1998. Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1, 203-219.
- De Jong, A., Verbeek, M. & Verwijmeren, P. 2011. Firms' debt-equity decisions when the static tradeoff theory and the pecking order theory disagree. *Journal of Banking & Finance*, 35, 1303-1314.
- Deangelo, H., Deangelo, L. & Stulz, R. M. 2010. Seasoned equity offerings, market timing, and the corporate lifecycle. *Journal of Financial Economics*, 95, 275-295.
- Denis, D. J. 1991. Shelf registration and the market for seasoned equity offerings. *Journal of Business*, 64, 189-212.
- Ding, B., Shawky, H. A. & Tian, J. 2009. Liquidity shocks, size and the relative performance of hedge fund strategies. *Journal of Banking & Finance*, 33, 883-891.
- Diro Ejara, D. & Ghosh, C. 2004. Underpricing and aftermarket performance of American depositary receipts (ADR) IPOs. *Journal of Banking & Finance*, 28, 3151-3186.
- Drucker, S. & Puri, M. 2005. On the Benefits of Concurrent Lending and Underwriting. *Journal of Finance*, 60, 2763-2799.
- Dunbar, C. G. 1995. The use of warrants as underwriter compensation in initial public offerings. *Journal of Financial Economics*, 38, 59-78.
- Eckbo, B. E. & Masulis, R. W. 1992. Adverse selection and the rights offer paradox. *Journal of Financial Economics*, 32, 293-332.
- Eckbo, B. E. & Masulis, R. W. 1995. Chapter 31 Seasoned equity offerings: A survey. In: R.A. Jarrow, V. M. & Ziemba, W. T. (eds.) *Handbooks in Operations Research and Management Science*. Elsevier.

- Eckbo, B. E., Masulis, R. W. & Norli, O. 2000. Seasoned public offerings: resolution of the 'new issues puzzle'. *Journal of Financial Economics*, 56, 251-291.
- Eckbo, B. E., Masulis, R. W. & Norli, Ø. 2007. Security Offerings. In: Eckbo, B. E. (ed.) *Handbook of Empirical Corporate Finance*. San Diego: Elsevier.
- Fabozzi, F. J. & Modigliani, F. 2003. *Capital Markets: institutions and instruments* 3rd ed., International ed. Upper Saddle River, N.J Pearson Education International, p65-67.
- Fama, E. F. & French, K. R. 2002. Testing Trade-Off and Pecking Order Predictions About Dividends and Debt. *Review of Financial Studies*, 15, 1-33.
- Fama, E. F. & French, K. R. 2005. Financing decisions: who issues stock? *Journal of Financial Economics*, 76, 549-582.
- Flannery, M. J. & Rangan, K. P. 2006. Partial adjustment toward target capital structures. *Journal of Financial Economics*, 79, 469-506.
- Frank, M. Z. & Goyal, V. K. 2003. Testing the pecking order theory of capital structure. *Journal of Financial Economics*, 67, 217-248.
- Garleanu, N. & Pedersen, L. H. 2007. Liquidity and Risk Management. *American Economic Review*, 97, 193-197.
- Garner, J. L. & Marshall, B. B. 2010. The non-7% solution. *Journal of Banking & Finance*, 34, 1664-1674.
- Geddes, R. 2005. Secondary equity offerings. *IPOs and Equity Offerings*. Oxford: Butterworth-Heinemann.
- Gerard, B. & Nanda, V. 1993. Trading and Manipulation Around Seasoned Equity Offerings. *Journal of Finance*, 48, 213-245.
- Graham, J. R. & Harvey, C. R. 2001. The theory and practice of corporate finance: evidence from the field. *Journal of Financial Economics*, 60, 187-243.
- Green, E. J. & Porter, R. H. 1984. Noncooperative Collusion under Imperfect Price Information. *Econometrica*, 52, 87-100.
- Habib, M. A. & Ljungqvist, A. P. 2001. Underpricing and Entrepreneurial Wealth Losses in IPOs: Theory and Evidence. *The Review of Financial Studies*, 14, 433-458.
- Hagerty, K. 1991. Equilibrium Bid-Ask Spreads i Markets with Multiple Assets. *Review of Economic Studies*, 58, 237.
- Hameed, A., Kang, W. & Viswanathan, S. 2010. Stock Market Declines and Liquidity. *Journal of Finance*, 65, 257-293.
- Hanley, K. W. 1993. The underpricing of initial public offerings and the partial adjustment phenomenon. *Journal of Financial Economics*, 34, 231-250.
- Hansen, R. S. 2001. Do investment banks compete in IPOs?: the advent of the "7% plus contract". *Journal of Financial Economics*, 59, 313-346.
- Hansen, R. S. & Crutchtey, C. 1990. Corporate earnings and financings: An empirical analysis. *Journal of Business*, 63, 347.
- Hao, Q. 2011. Securities litigation, withdrawal risk and initial public offerings. *Journal of Corporate Finance*, 17, 438-456.
- Hertzel, M. G. & Li, Z. 2010. Behavioral and Rational Explanations of Stock Price Performance around SEOs: Evidence from a Decomposition of Market-to-Book Ratios. *Journal of Financial & Quantitative Analysis*, 45, 935-958.
- Hoberg, G. 2007. The Underwriter Persistence Phenomenon. *The Journal of Finance*, 62, 1169-1206.

- Hovakimian, A. & Hutton, I. 2010. Market Feedback and Equity Issuance: Evidence from Repeat Equity Issues. *Journal of Financial and Quantitative Analysis*, 45, 739-762.
- Hovakimian, A., Opler, T. & Titman, S. 2001. The Debt-Equity Choice. *The Journal of Financial and Quantitative Analysis*, 36, 1-24.
- Huang, M. 2003. Liquidity shocks and equilibrium liquidity premia. *Journal of Economic Theory*, 109, 104-129.
- Huang, R. & Zhang, D. 2011. Managing Underwriters and the Marketing of Seasoned Equity Offerings. *Journal of Financial & Quantitative Analysis*, 46, 141-170.
- Hull, J. C. 2006. *Options, Futures and Other Derivatives 6th Edition*, Upper Saddle River, N.J., Pearson/Prentice Hall, p286-287, p300.
- Ibbotson, R. G. & Ritter, J. R. 1995. Chapter 30 Initial public offerings. In: R.A. Jarrow, V. M. & Ziemba, W. T. (eds.) *Handbooks in Operations Research and Management Science*. Elsevier.
- Jegadeesh, N., Weinstein, M. & Welch, I. 1993. An empirical investigation of IPO returns and subsequent equity offerings. *Journal of Financial Economics*, 34, 153-175.
- Jensen, M. C. & Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3, 305-360.
- Jenter, D., Lewellen, K. & Warner, J. B. 2011. Security Issue Timing: What Do Managers Know, and When Do They Know It? *The Journal of Finance*, 66, 413-443.
- Jeon, J. Q. & Ligon, J. A. 2011. The role of co-managers in reducing flotation costs: Evidence from seasoned equity offerings. *Journal of Banking & Finance*, 35, 1041-1056.
- Jung, K., Kim, Y.-C. & Stulz, R. M. 1996. Timing, investment opportunities, managerial discretion, and the security issue decision. *Journal of Financial Economics*, 42, 159-185.
- Kalay, A. & Shimrat, A. 1987. Firm value and seasoned equity issues : Price pressure, wealth redistribution, or negative information. *Journal of Financial Economics*, 19, 109-126.
- Kalev, P. S., Pham, P. K. & Wong, S. 2006. Underpricing, liquidity and the cost of seasoned equity offers. *Working paper, Monash University, Australia*.
- Katherine Spiess, D. & Pettway, R. H. 1997. The IPO and first seasoned equity sale: Issue proceeds, owner/managers' wealth, and the underpricing signal. *Journal of Banking & Finance*, 21, 967-988.
- Kim, D., Palia, D. & Saunders, A. 2010. Are Initial Returns and Underwriting Spreads in Equity Issues Complements or Substitutes? *Financial Management (Blackwell Publishing Limited)*, 39, 1403-1423.
- Kim, K. A. & Shin, H.-H. 2004. The Puzzling Increase in the Underpricing of Seasoned Equity Offerings. *Financial Review*, 39, 343-365.
- Kim, Y. & Park, M. S. 2005. Pricing of Seasoned Equity Offers and Earnings Management. *Journal of Financial & Quantitative Analysis*, 40, 435-463.
- Korajczyk, R. A., Lucas, D. J. & McDonald, R. L. 1991. The Effect of Information Releases on the Pricing and Timing of Equity Issues. *The Review of Financial Studies*, 4, 685-708.
- Krasker, W. S. 1986. Stock Price Movements in Response to Stock Issues under Asymmetric Information. *The Journal of Finance*, 41, 93-105.

- Kyle, A. S. 1985. CONTINUOUS AUCTIONS AND INSIDER TRADING. *Econometrica*, 53, 1315-1335.
- Kyle, A. S. & Xiong, W. 2001. Contagion as a Wealth Effect. *Journal of Finance*, 56, 1401-1440.
- Leary, M. T. & Roberts, M. R. 2010. The pecking order, debt capacity, and information asymmetry. *Journal of Financial Economics*, 95, 332-355.
- Lease, R. C., Masulis, R. W. & Page, J. R. 1991. An Investigation of Market Microstructure Impacts on Event Study Returns. *Journal of Finance*, 46, 1523-1536.
- Lee, G. & Masulis, R. W. 2009. Seasoned equity offerings: Quality of accounting information and expected flotation costs. *Journal of Financial Economics*, 92, 443-469.
- Lee, I., Lochhead, S., Ritter, J. & Quanshui, Z. 1996. THE COSTS OF RAISING CAPITAL. *Journal of Financial Research*, 19, 59.
- Lee, K.-H. 2011. The world price of liquidity risk. *Journal of Financial Economics*, 99, 136-161.
- Lee, M.-L. & Chiang, K. C. H. 2004. Substitutability between Equity REITs and Mortgage REITs. *Journal of Real Estate Research*, 26, 95-113.
- Leland, H. E. & Pyle, D. H. 1977. INFORMATIONAL ASYMMETRIES, FINANCIAL STRUCTURE, AND FINANCIAL INTERMEDIATION. *Journal of Finance*, 32, 371-387.
- Li, X. & Masulis, R. W. 2007. Venture capital investment by IPO underwriters: certification, alignment of interest, or moral hazard? . *Unpublished Working Paper, Vanderbilt University, Nashville, TN*.
- Liu, W. 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82, 631-671.
- Liu, X. & Ritter, J. R. 2011. Local underwriter oligopolies and IPO underpricing. *Journal of Financial Economics*, 102, 579-601.
- Liu, Y. & Malatesta, P. H. 2005. Credit ratings and the pricing of seasoned equity offerings. *Unpublished Working Paper, University of Washington, Seattle, WA*.
- Ljungqvist, A. & Wilhelm, W. J. 2003. IPO Pricing in the Dot-com Bubble. *The Journal of Finance*, 58, 723-752.
- Loderer, C. F., Sheehan, D. P. & Kadlec, G. B. 1991. The pricing of equity offerings. *Journal of Financial Economics*, 29, 35-57.
- Loughran, T. & Ritter, J. 2004. Why Has IPO Underpricing Changed Over Time? *Financial Management (Blackwell Publishing Limited)*, 33, 5-37.
- Loughran, T. & Ritter, J. R. 1995. The New Issues Puzzle. *Journal of Finance*, 50, 23-51.
- Loughran, T. & Ritter, J. R. 2002. Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? *Review of Financial Studies*, 15, 413-443.
- Loughran, T. I. M. & Ritter, J. R. 1997. The Operating Performance of Firms Conducting Seasoned Equity Offerings. *Journal of Finance*, 52, 1823-1850.
- Lowry, M., Officer, M. S. & Schwert, G. W. 2010. The Variability of IPO Initial Returns. *The Journal of Finance*, 65, 425-465.
- Lyandres, E., Sun, L. & Zhang, L. 2008. The New Issues Puzzle: Testing the Investment-Based Explanation. *Review of Financial Studies*, 21, 2825-2855.
- Mahajan, A. & Tartaroglu, S. 2008. Equity market timing and capital structure: International evidence. *Journal of Banking & Finance*, 32, 754-766.

- Marquardt, C. A. & Wiedman, C. I. 1998. Voluntary Disclosure, Information Asymmetry, and Insider Selling through Secondary Equity Offerings. *Contemporary Accounting Research*, 15, 505-537.
- Masulis, R. W. 1983. The Impact of Capital Structure Change on Firm Value: Some Estimates. *Journal of Finance*, 38, 107-126.
- Masulis, R. W. & Korwar, A. N. 1985. Seasoned equity offerings : An empirical investigation. *Journal of Financial Economics*, 15, 91-118.
- McNichols, M. F. 2002. DISCUSSION OF The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *Accounting Review*, 77, 61.
- Meggison, W. L. & Weiss, K. A. 1991. Venture Capitalist Certification in Initial Public Offerings. *Journal of Finance*, 46, 879-903.
- Mikkelson, W. H. & Partch, M. M. 1985. Stock price effects and costs of secondary distributions. *Journal of Financial Economics*, 14, 165-194.
- Miller, M. H. & Rock, K. 1985. Dividend Policy under Asymmetric Information. *Journal of Finance*, 40, 1031-1051.
- Modigliani, F. & Merton, H. M. 1958. The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review*, 48, 261-297.
- Mola, S. & Loughran, T. 2004. Discounting and Clustering in Seasoned Equity Offering Prices. *Journal of Financial & Quantitative Analysis*, 39, 1-23.
- Moulton, P. C. & Wei, L. 2009. A tale of two time zones: The impact of substitutes on cross-listed stock liquidity. *Journal of Financial Markets*, 12, 570-591.
- Myers, S. C. & Majluf, N. S. 1984. CORPORATE FINANCING AND INVESTMENT DECISIONS WHEN FIRMS HAVE INFORMATION THAT INVESTORS DO NOT HAVE. *Journal of Financial Economics*, 13, 187-221.
- Nelson, D. B. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 347-370.
- Parsons, J. E. & Raviv, A. 1985. Underpricing of seasoned issues. *Journal of Financial Economics*, 14, 377-397.
- Pástor, L. & Stambaugh, R. F. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111, 642-685.
- Puri, M. 1999. Commercial banks as underwriters: implications for the going public process. *Journal of Financial Economics*, 54, 133-163.
- Rhodes-Kropf, M., Robinson, D. T. & Viswanathan, S. 2005. Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics*, 77, 561-603.
- Ritter, J. R. 1984. The "Hot Issue" Market of 1980. *The Journal of Business*, 57, 215-240.
- Rock, K. 1986. Why new issues are underpriced. *Journal of Financial Economics*, 15, 187-212.
- Ross, S. A., Westerfield, R. W. & Jaffe, J. F. 2006. *Corporate Finance* 7th ed. Boston, Mass., McGraw-Hill/Irwin, , p374, p384-388, p544-545, p847.
- Sadka, R. 2006. Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, 80, 309-349.
- Safieddine, A. & Wilhelm, W. J. 1996. An Empirical Investigation of Short-Selling Activity Prior to Seasoned Equity Offerings. *Journal of Finance*, 51, 729-749.
- Scholes, M. S. 1972. The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices. *Journal of Business*, 45, 179-211.

- Sherman, A. E. & Titman, S. 2002. Building the IPO order book: underpricing and participation limits with costly information. *Journal of Financial Economics*, 65, 3-29.
- Shyam-Sunder, L. & Myers, C. S. 1999. Testing static tradeoff against pecking order models of capital structure. *Journal of Financial Economics*, 51, 219-244.
- Silber, W. L. 1975. THINNESS IN CAPITAL MARKETS: THE CASE IF THE TEL AVIV STOCK EXCHANGE. *Journal of Financial & Quantitative Analysis*, 10, 129-142.
- Singh, A. K. 1992. Common stock rights offering and the standby underwriting contract. Working paper: Iowa State University.
- Smith, C. W. 1977. Alternative methods for raising capital : Rights versus underwritten offerings. *Journal of Financial Economics*, 5, 273-307.
- Smith, C. W. J. 1986. INVESTMENT BANKING AND THE CAPITAL ACQUISITION PROCESS. *Journal of Financial Economics*, 15, 3-29.
- Stephen Morris & Shin, H. S. 2004. Liquidity Black Holes. *Review of Finance*, 8, 1-18.
- Taggart, R. A., Jr. 1977. A Model of Corporate Financing Decisions. *The Journal of Finance*, 32, 1467-1484.
- Walker, M. D. & Yost, K. 2008. Seasoned equity offerings: What firms say, do, and how the market reacts. *Journal of Corporate Finance*, 14, 376-386.
- Watanabe, A. & Watanabe, M. 2008. Time-Varying Liquidity Risk and the Cross Section of Stock Returns. *Review of Financial Studies*, 21, 2449-2486.
- Welch, I. 1992. Sequential Sales, Learning, and Cascades. *The Journal of Finance*, 47, 695-732.
- Welch, I. V. O. 1989. Seasoned Offerings, Imitation Costs, and the Underpricing of Initial Public Offerings. *Journal of Finance*, 44, 421-449.
- Xiong, W. 2001. Convergence trading with wealth effects: an amplification mechanism in financial markets. *Journal of Financial Economics*, 62, 247-292.
- Yeoman, J. C. 2001. The optimal spread and offering price for underwritten securities. *Journal of Financial Economics*, 62, 169-198.

APPENDICES

Appendix 1

Figure 1 **Global Seasoned Equity Offerings, Total Deal Value by Type (1991-2004)**

This chart shows the evolution of global seasoned equity offerings for the 1991-2004 period. The series refer to the total deal value (in constant US\$2004 billions) raised by accelerated (mixed and pure) bookbuilt offerings (ABO), block trades, bought deals and all other types of non accelerated transactions.

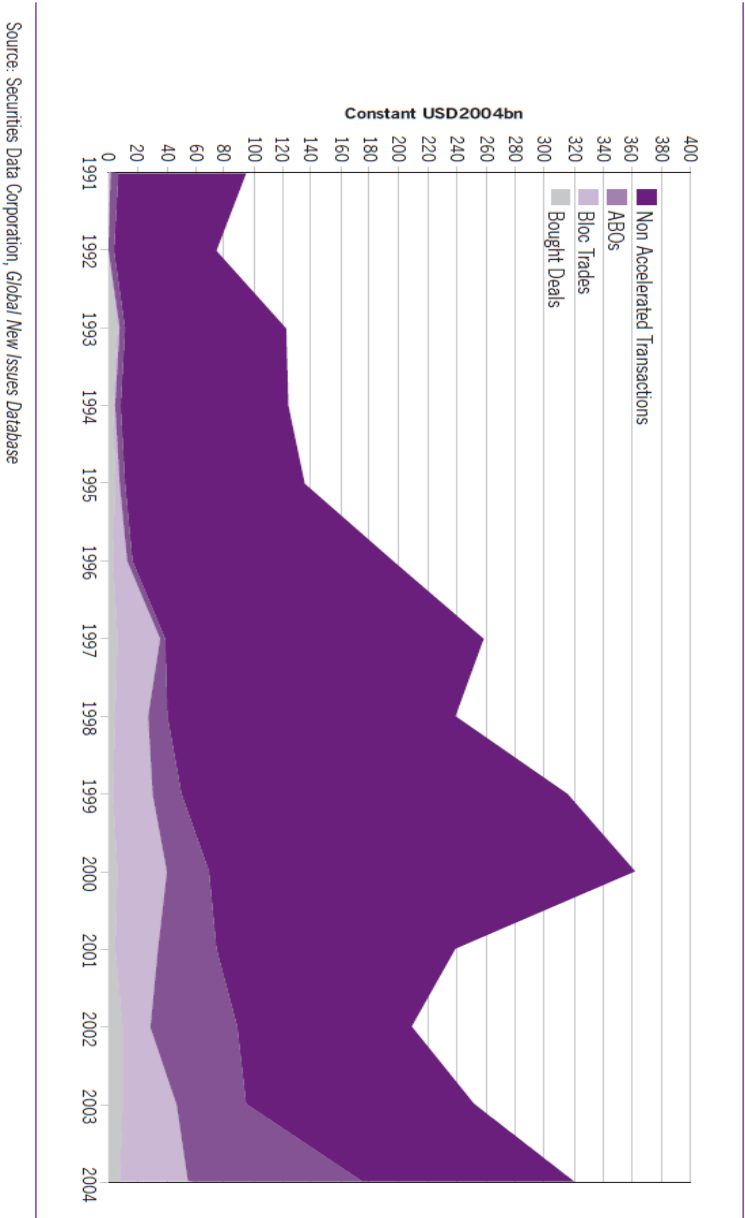


Figure A-1 Global Seasoned Equity Offerings, Total deal Value by Type
(Securities Data Corporation, 2004 cited in Bortolotti and Smart, 2008, p.38)

Appendix 2

Table A-1 Top 10 Banks by Fees

Fees	Change in Fees	% of Fees collected by product in 2010				
Top 10 Banks	(\$m)	vs. Prev Period*	M&A	Equity	Bonds	Loans
JP Morgan	5,533.85	-3%	25	27	31	17
Bank of America Merrill Lynch	4,581.59	-1%	19	25	34	21
Goldman Sachs	4,386.52	+11%	44	29	22	4
Morgan Stanley	4,055.48	+13%	35	36	24	5
Credit Suisse	3,379.12	+19%	30	27	33	10
Deutsche Bank	3,286.80	+15%	25	24	38	12
Citi	3,238.67	-11%	22	25	41	12
Barclays Capital	2,864.44	+29%	24	20	42	14
UBS	2,614.44	+6%	32	37	25	6
BNP Paribas	1,433.89	-9%	21	11	39	29
Total	83,356.94	+15%	37	26	24	13

(<http://markets.ft.com/investmentBanking/tablesAndTrends.asp>)

Appendix 3

A 3.1. Limit Order Model Discussions

In this section, a derivation of the limit order model from Chacko, Jurek and Stafford (2008) is summarized. According to the previous discussion, the baseline model depends on three factors: (1) market structure; (2) arrival rate of opposing order; (3) the evolution of the fundamental value. Because these factors have complex dynamics in reality, the limit order model is constructed as a reduced-form.

For fundamental value, the dynamics are described by:

$$\frac{dV_t}{V_t} = \mu dt + \sigma dZ_t, \quad (A1)$$

where μ and σ^2 are the instantaneous expected return and variance of the fundamental value, and dZ_t is a standard Gauss-Wiener process.

A limit order, $L^i(Q, K)$, specifies a quantity (Q), price (K), and direction of trade (i.e., buy or sell, $i \in \{B, S\}$). The arrival rate of opposing order flow, $\lambda^i(Q)$, is a function of the order quantity, Q .

Let $L(V_t, Q, K, t)$ denote the time t value of a Q -share limit order with a limit price of K .

The evolution of the limit order's value is:

$$dL(V_t, Q, K, t) = \lim_{\Delta t \rightarrow 0} \left[\pi(t, t + \Delta t) \cdot (L(V_{t+\Delta t}, Q, K, t) - L(V_t, Q, K, t)) + \right. \\ \left. (1 - \pi(t, t + \Delta t)) \cdot (0 - L(V_t, Q, K, t)) \right] \quad (A2)$$

Formula (A2) then can be deducted to

$$L_F \cdot (rF_{Q,t}) + \frac{1}{2} L_{FF} \cdot (\sigma F_{Q,t})^2 - (r + \lambda^i(Q))L = 0, \quad (A3)$$

where $F_{Q,t} = Q \cdot V_t$

The ODE is an equidimensional equation that has the solution calculated by a linear combination of power functions,

$$L^j(V_t, Q, K, t) = \alpha_0 F_{Q,t}^{\phi_+} + \alpha_1 F_{Q,t}^{\phi_-}, \quad (\text{A4})$$

α_0 and α_1 are two constants of integration that can be determined from the boundary conditions. j is used to represent sell and buy limit orders ($j=S$ means sell). The value L depends on the quantity dependent arrival intensity, $\lambda^i(Q)$, of buy (sell) market orders through the power coefficient, $\phi_{\pm}(\lambda^i)$.

To solve $\phi_{\pm}(\lambda^i)$, substitute the guess $F_{Q,t}^{\phi}$ into (A4)

$$L^j(V_t, Q, K, t) = (\alpha_0 + \alpha_1) F_{Q,t}^{\phi}, \quad (\text{A5})$$

Substitute (A5) into (A3) gives

$$\frac{\sigma^2}{2} \phi^2 + (r - \frac{\sigma^2}{2}) \phi - (r + \lambda^i(Q)) = 0. \quad (\text{A6})$$

The power coefficients are given by the roots of this equation:

$$\phi_{\pm}(\lambda^i) = \left(\frac{1}{2} - \frac{r}{\sigma^2} \right) \pm \sqrt{\left(\frac{1}{2} - \frac{r}{\sigma^2} \right)^2 + \frac{2(r + \lambda^i(Q))}{\sigma^2}}. \quad (\text{A7})$$

Economic intuition allows us to exclude one of the two roots in the case of both a sell limit order and a buy limit order. In particular, since the value of a sell (buy) limit order is increasing (decreasing) in $F_{Q,t}$, we can exclude the negative (positive) root.

The next is to identify α_0 and α_1 , then the solution of L is obtained.

The constants of integration, (α_0, α_1) can be identified by imposing the boundary conditions. Take S (sell limit order) for example.

The boundary conditions are:

$$\lim_{V_t \downarrow 0} L^S = 0 \quad (\text{A8})$$

$$\lim_{V_t \uparrow V^*} L^S = Q \cdot (V^* - K) \quad (\text{A9})$$

$$\lim_{V_t \uparrow V^*} L_F^S = 1, \quad (\text{A10})$$

where V^* is the optimal exercise thresholds for sell limit orders.

(A8) indicates that the call option becomes worthless as the value of the underlying tends to zero and requires that $\alpha_1 = 0$.

(A9), (A10) correspond respectively to the value matching and smooth pasting conditions at the optimal exercise threshold, V^* .

From (A9): $\lim_{V_t \uparrow V^*} (\alpha_0 F_{Q,t}^{\phi_+}) = Q \cdot (V^* - K)$,

$$\alpha_0 (V^* Q)^{\phi} = Q \cdot (V^* - K). \quad (\text{A11})$$

From (A10): $\lim_{V_t \uparrow V^*} L_F^S = 1$

$$\alpha_0 \phi (V^* Q)^{\phi-1} = 1. \quad (\text{A12})$$

Combining (A11) and (A12) gives

$$V^* = K \cdot \left(\frac{\phi_+(\lambda^B)}{\phi_+(\lambda^B) - 1} \right), \quad (\text{A13})$$

Substituting above equation into (A12) gives $\alpha_0 = \frac{1}{\phi_+(\lambda^B) \left(\frac{\phi_+(\lambda^B) K Q}{\phi_+(\lambda^B) - 1} \right)^{\phi-1}}$.

Substituting above equation into (A4) gives

$$L^S(V_t, Q, K, t) = \frac{QK}{\phi_+(\lambda^B) - 1} \cdot \left(\frac{\phi_+(\lambda^B) - 1}{\phi_+(\lambda^B)} \cdot \frac{V_t}{K} \right)^{\phi_+(\lambda^B)}, \quad V_t < V^*. \quad (\text{A14})$$

And it is optimal for the market maker to exercise the implicit call option whenever

fundamental value reaches the threshold $V^* = K \cdot \left(\frac{\phi_+(\lambda^B)}{\phi_+(\lambda^B) - 1} \right)$ from below.

To induce immediate exercise of a sell limit order, the optimal exercise threshold price V^* should be set equal to the prevailing fundamental value V_t .

Therefore from (A13), the bid price is

$$K_B(Q) = V_t \cdot \left(\frac{\phi_+(\lambda^B) - 1}{\phi_+(\lambda^B)} \right). \quad (\text{A15})$$

The percentage immediacy costs for sales and purchases are given by

$$\frac{K_B(Q) - V_t}{V_t} = -\frac{1}{\phi_+(\lambda^B)}. \quad (\text{A16})$$

In particular, whenever $\lambda^i(Q) \gg r$, $\phi_{\pm}(\lambda^i) \approx \pm \frac{\sqrt{2\lambda^i(Q)}}{\sigma}$.

Therefore, the percentage immediacy cost is

$$p(Q) \approx \sigma \sqrt{\frac{Q}{2\lambda}}.$$

A 3.2. The Application of Limit Order Model in SEO Underpricing

Altinkilic and Hansen (2003) divide the SEO discounting into expected and surprise components and argue that the surprise component reflects the lead bank's final adjustment to the offer price. Similarly, Mola and Loughran (2004) find evidence that underwriters tend to set an offer price at the closing market price, but rounded down to a near but not necessarily the next integer. Chapter Five and Six in this PhD study also confirm that, even after offer dates adjustment, the trend of setting offer price at the next or other lower integer still holds. All these findings suggest that investment banks often make a final adjustment to the offer price based on the closing market price prior to the offer date. As discussed in Chapter Six, price pressure is a possible explanation for SEO underpricing. In this section, a new measure of price pressure, derived from the limit order model, is introduced. To apply the structure model to measure the price pressure, two hypotheses are required. The first hypothesis is discussed in the following section.

A 3.3. The Immediacy Cost and Price Pressure

Hypothesis One: (part of) the price pressure faced by underwriters in a SEO transaction can be regarded as the immediacy cost for selling a block of shares, and part of SEO underpricing is used to compensate this immediacy cost.

Hypothesis one has some support from both established hypotheses and empirical evidence. First, the role of underwriters in equity issuance is analogue to that of market makers in stock transactions. Butler, Grullon and Weston (2005) suggest that underwriters have a similar role to market makers who line up buyers and sellers to facilitate the intermediation process. Both market makers and underwriters face inventory risk. In stock transactions, market makers face this risk, especially when having to sell a block of illiquid shares. When the inventory risk is high, market makers would require a high bid-ask spread as compensation. Sellers (buyers) who are eager to sell (buy) their shares immediately would accept this charge. Therefore, the cost is regarded as immediacy cost by Chacko et al.(2008) and it might be estimated using the limit model discussed in Chapter Three. In an SEO transaction, when a firm-commitment underwritten contract is signed, the underwriter is obliged to buy the shares at a fixed price. If there is an unexpected reduction in investor demand for the SEO, the investment banks will bear the inventory risk.

In contrast with a market maker, the underwriter has two ways to cover this immediacy cost. One is underwriting spread or gross spread, which is a percentage of the offer price. The other is SEO underpricing. Butler et al. (2005) note that underwriting spreads have a significantly positive relation with the liquidity of underlying shares. The higher the liquidity is, the less the inventory risk and the

associated immediacy cost if the immediacy cost is covered by gross spread. This immediacy cost is regarded as the compensation for the inventory risk for the underwriter. However, the underwriting spread is charged based on the offer price. Before considering underwriting spread, the underwriter still can use the underpricing to cover part of the immediacy cost, only in this case the immediacy cost can be regarded as (part of) the effects of price pressure. Because the underpricing is directly related to the offer price that could affect the demand for the shares from investors, it might be a more efficient way to cover the immediacy cost.

The empirical evidence is from the expression of immediacy cost derived from the limit order model. The analytical result of immediacy cost is $\sigma \sqrt{\frac{Q}{2\lambda}}$, where σ is the volatility of the underlying shares defined as the return standard deviation. As discussed in Chapter Two and Chapter Six, stock return volatility is proved to be positively related to SEO underpricing at statistically significant level (Altinkilic and Hansen, 2003; Corwin, 2003; Kim and Shin, 2004). This relationship is consistent with the limit order model in which the volatility also has positive effects on the immediacy cost. Furthermore, $\sqrt{\frac{Q}{2\lambda}}$ is used to represent the impact of transaction size.

Q is the total number of the shares in the order and λ is the arrival rate of the opposite order. Chacko et al.(2008) and (2006) suggest that the arrival rate could be estimated using historical trading data. This suggestion coincides with an alternative measure of price pressure used by Corwin (2003)⁹⁰. This measure is also regarded as an alternative proxy for relative offer size, defined as offered shares divided by average

⁹⁰ The alternative measure is mention in Footnote 12 in Corwin (2003).

daily (adjusted) trading volume. Corwin's conclusions are not affected by the use of this measure. In other words, the alternative proxy Q/λ has a positive relation with SEO underpricing. In sum, both parts of the immediacy cost σ and $\sqrt{\frac{Q}{2\lambda}}$ are positively related to SEO underpricing, indicating that SEO underpricing might include the immediacy cost.

A 3.4. Assumptions and Parameter Estimation of the Limit Order Model

As discussed in Chapter Two, the limit order model requires several assumptions and four variables to calculate the immediacy cost⁹¹. After checking the underlying assumptions of the limit order model, it can be concluded that the SEO process satisfies the underlying assumptions to some extent. In this section, the assumptions of limit order model are discussed in the context of SEO process. The estimations of those variables are also discussed as follows.

Assumption 1: Market structure. First of all, the market structure of a price driven system required by the limit order model is similar to the pattern in the SEO process. The issue of equity is set at the offering price; it is available for both investors and underwriters. However, the demand from each investor might vary according to other factors. The investment banks are in the position to provide reliable liquidity in a firm commitment contract. The monopolist position of market maker is similar to that of a syndicate in SEO pricing. As discussed previously, investment banks have the privileged position in an SEO process. They link the issuer and investors. If the

⁹¹ In a simplified form, the model requires three variables to get the result.

demand from investors cannot take all the shares in the offering, investment banks have the advantage of taking these shares at a discounted price first, then reselling them into the market. This intermediate function is same as the role of market maker in the price-driven market.

Assumption 2: in the theory, the issuer of the equity has no patience. The limit order model requires the party who initiates the deal to be impatient and complete the deal immediately. As discussed in Chapter Two, the offer price, and other profit-sharing agreements are decided one day prior to the issue. If the underwriter and the issuer cannot reach a deal, the SEO would face cancellation or postponement in a firm commitment transaction. In a best efforts offer (which is rare in SEOs), if the shares cannot be sold at offering price, the unsold shares would be withdrawn by the firm. Both cases are regarded as the issue failure. If the cancellations or postponements of SEOs occur, the issuer will lose registration fees, accounting expenses and management time devoted to the offering process. Due to the cost of the failure, SEO cancellations or postponements rarely occur (Mikkelson and Partch, 1988). Therefore, it can be reasonably assumed that issuers of SEOs have no patience in normal circumstances since, for a unified final price set for all members in the syndicate, the SEO can be regarded as a ‘one-shot execution’. Both above conditions in an SEO emphasize the role of immediacy cost in SEO pricing.

However, the cancellation of SEOs is slightly different from the pattern of a limit order model. In a limit order, the seller can still withdraw the limit order after the order is set but in an SEO transaction, before setting the offer price, the firm can cancel or postpone the offering – but once the offer price is set on the issue day, it can

no longer be cancelled. In a firm commitment offer, the unsold shares should be taken by the investment banks. In other words, unlike a seller who can withdraw the order even after setting the price, an issuer has no right to withdraw the deal once it has been made. However, as discussed, the limit order model assumes that the transaction initiator has no patience. As a result, the offer price set by the underwriter is taken almost immediately by the transaction initiator (or the issuer) in the equity offering transaction. Therefore, the slight difference in the aspect of withdrawal setting might not have any substantial impact on the application of a limit order model on SEO transactions.

Parameter Estimation

To summarize, the SEO process satisfies the major assumptions required by the limit order model. Therefore, it might be used as a base model in measuring immediacy cost or price pressure. As discussed before, the discount given by the limit order model is,

$$p(Q) = \frac{K_B(Q, \alpha = 0) - V_t}{V_t} = -\frac{1}{\phi_+(\lambda^B)},$$

$$\text{where } \phi_+(\lambda^B) = \left(\frac{1}{2} - \frac{r}{\sigma^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r}{\sigma^2}\right)^2 + \frac{2(r + \lambda^i(Q))}{\sigma^2}}.$$

σ : the volatility of a firm's fundamental value is estimated using the standard deviation of its daily stock returns over a specific period (e.g. one year).

Q : the offer size of the issue.

λ : arrival rate of opposing order in the primary market.

There are four parameters to estimate, namely order size, volatility, risk free rate and the arrival rate of opposing order $\lambda^i(Q)$. The offer size is given by the SDC database. To estimate the risk free rate and volatility, there are available methods in the literature. The yield on 1-month Treasury bills is taken as the prevailing risk free rate. The volatility of the underlying shares can be estimated using two methods suggested by Hull (2006). One is to estimate volatilities from historical data. Specifically, the volatility is defined as the standard deviation of stock return over a certain period.

The other method is to calculate implied volatilities based on the Black-Scholes pricing formulae. However, only a small portion of SEO issuing firms has listed options. For instance, Kim and Shin (2004) find only 5.54% of their SEO firms have listed options during the sample period. Safieddine and Wilhelm (1996) report that 97 out of the 476 SEO firms in their sample have listed options. Therefore, due to data availability, the volatility can only be estimated from historical data in this PhD study. In this section, the volatility follows the definition in previous chapters – the standard deviation of daily returns over 30 trading days ending 11 days prior to the offer. Moreover, because risk free rate is much smaller than the arrival rate of opposing order, the expression of immediacy can be approximated as $p(Q) = \sigma \sqrt{\frac{Q}{2\lambda}}$. As a result, only the volatility and the arrival rate of opposing order need to be estimated.

Estimation of the arrival rate of opposing order λ

It is quite difficult to estimate the arrival rate of an opposing order in the limit order transaction. As discussed in the literature, the arrival rate of opposing order is critical for the limit order model. In Chacko, Jurek and Stafford (2008), the arrival rate of

opposing order is estimated by two methods. Both methods assume that the arrival rate of an opposing order is the simple function of offer size Q : $\lambda^B(Q) = \lambda^B(1) \cdot Q^{-1}$. The arrival rate of expected waiting time for the completion of a Q -share order is precisely Q times larger than the corresponding waiting time for a one-share order. To ensure this setting, they examine the scaling order with respect to quantity by estimating the following nonlinear least squares regression, $E[\tau^i(Q)] = \alpha_0 + \alpha_1 \cdot Q^n$. The sample consists of 1,488 firms and the mean estimate of n is close to 1. Thus, they conclude that the above setting is reasonable.

As for the estimation methods, one is ‘the naive’ method, which is illustrated in the working paper by Chacko, Jurek and Stafford (2006). To estimate waiting time for a one-share order, one simply takes the total amount of time that has elapsed and divides it by the total realized volume. For instance, if the daily trading volume of a share is 1000, the estimate waiting time for a one-share order is 1/1000 day. And the expected waiting time for an offer with 1000 shares is 1 day. The other method is the implied method. It uses historical data to imply the order arrival rate. Chacko, Jurek and Stafford (2008) implement this method to calibrate the arrival rate in estimation of transaction costs for NYSE Firms. They use the quantity cross-section of the realized percentage transaction costs and imply out the order arrival rate. Then they effectively produce a transaction cost function for use at the end of the year.

In an SEO transaction, the arrival rate of an opposing order in an SEO transaction (the primary market) reflects the information gathered by the book building process in SEO pricing practice. As discussed in Chapter Two, the lead underwriters usually

gather bid information from investors through the book building process to decide the offering price. Therefore, the arrival rate directly measures the demand for the seasoned equity in the book building process. However, in an SEO transaction, the price pressure effects only represent a portion of SEO underpricing. Therefore, the implied method cannot be implemented. The naive estimation uses the average daily volume of the underlying shares to measure the arrival rate. The estimation of arrival rate in the primary market is an attempt to estimate demand information prior to the offer date. However, in SEO pricing, the demand for the seasoned equity is separated from the secondary market. The shares are traded in the primary market in which the participants are mainly institutional investors. Indeed, it is almost impossible to measure the arrival rate in the primary market 1 day prior to the offering. Then the second hypothesis is need.

Hypothesis Two: the arrival rate in the primary market is highly related to the trading volume in the secondary market.

The underlying notion behind this hypothesis is that if there is a strong demand in the secondary market, the demand can be satisfied by bidding in the primary market.

Because λ is calibrated using trading volume in the secondary market, the number calibrated by $\sigma\sqrt{\frac{Q}{2\lambda}}$ cannot be regarded as the immediacy cost directly. However, if

Hypothesis Two holds, the variable $\sigma\sqrt{\frac{Q}{2\lambda}}$ might be a more precise measure to reflect temporary price pressure.

A 3.5. Testing Results of Limit Order Model

$$\begin{aligned} \text{Underpricing} = & \beta_0 + \beta_1 \text{GrossSpread} + \beta_2 \text{Volatility} + \beta_3 \text{CARPos} + \beta_4 \text{CARNeg} + \beta_5 \text{LnPrice} \\ & + \beta_6 \text{CLUSTER} + \beta_7 \text{CloseBidDiffNY} + \beta_8 \text{CloseBidDiffNas} \\ & + \beta_9 \text{NASDAQDummy} + \beta_{10} \text{Underwriter} + \beta_{11} \text{Toptier} \end{aligned}$$

The base model for the regression test is similar to that in Chapter Six. If the immediacy cost is taken into consideration, then relative offer size and volatility should be removed from the base model because the expression of immediacy cost already includes volatility and the offer size factors. In this section, we compare the regression results of the base model with those of models that include immediacy cost.

The immediacy costs is expressed as $\sigma \sqrt{\frac{Q}{2\lambda}}$. As discussed earlier, daily volumes of the underlying shares are utilized to estimate the arrival rate of opposing orders. We use the average daily volume calculated from 5 trading days, 11 trading days, and 30 trading days prior to the issue to estimate immediacy cost. As for NASDAQ issues, the volume is divided by two.

The regression results are presented in Table A-2. These suggest that there is no statistically significant relation between immediacy costs and SEO underpricing (R^2). Three variables immediacy cost (30days), immediacy cost (11days) and immediacy cost (5days); all have insignificant coefficients. Among them, only immediacy cost (30days) has positive coefficients. The other two variables even have negative coefficients, showing a completely reverse relation compared with the hypothesised relation. Among all these models, Model 1 has the highest adjusted R^2 . This result shows that when immediacy cost is incorporated, the overall explanation power does

not improve but declines. All this suggests that incorporating immediacy cost into the existing models generates unfavourable results.

As discussed earlier, the most likely explanation for the undesirable results is that Hypothesis Two is inconsistent with the real case. The arrival rate in the primary market cannot be estimated using the volume data in the secondary market. For instance, in the limit order model, the size of the order is completely unexpected by the market – therefore, the daily volume from the secondary market may be a suitable estimation for the arrival rate of the opposing order. However, in an SEO transaction, the deal is often announced several months before the issue date, therefore, investors are well informed about the deal. The awareness of the offer size would make it unsuitable to estimate the arrival rate of opposing order based on the daily volume.

However, even Hypothesis Two might be not correct and, in the future research, there might be a chance that the bid information collected from the book building process can be used to estimate the arrival rate of opposing order in the primary market⁹². For example, in the book building process, above a specific price (e.g. the prior closing price), the subscribed volume is *Size 1* below the offer size-*Size 2*, then the size of unexpected part of the offering should be (*Size 2-Size 1*). Thus, in the limit order model, (*Size 2-Size 1*) should be regarded as the order size and arrival rate of the opposing order can be estimated from trading volume in the secondary market.

⁹² Although the information gathered from the book building process is confidential, the limit order model still has a chance to be utilized by these underwriters themselves.

Table A-2 OLS Regression results for SEO underpricing (with Immediacy Cost)

Model	1	2	3	4
Volatility	0.2865*** (12.95)			
Reloffersize	0.0071** (2.53)			
Immediacy Cost (30days)		0.3821 (1.19)		
Immediacy Cost (11days)			-0.5013 (-1.55)	
Immediacy Cost (5days)				-0.2576 (-0.91)
GrossSpreadPercent	-0.0023*** (-4.78)	-0.0018*** (-3.80)	-0.0017*** (-3.52)	-0.0017*** (-3.61)
CARPos	0.0769*** (7.76)	0.1082*** (11.03)	0.1079*** (11.00)	0.1075*** (10.96)
CARNeg	-0.0181** (-2.03)	-0.0497*** (-5.67)	-0.0517*** (-5.93)	-0.0511*** (-5.87)
LnPrice	-0.0166*** (-20.02)	-0.0165*** (-19.73)	-0.0166*** (-19.97)	-0.0166*** (-19.92)
CLUSTER	0.0124*** (12.74)	0.0136*** (13.81)	0.0136*** (13.82)	0.0136*** (13.80)
CloseBidDiffNYSE	0.0915 (0.71)	0.0937 (0.72)	0.1002 (0.77)	0.0982 (0.75)
CloseBidDiffNas	0.4742*** (14.07)	0.4771*** (13.23)	0.5096*** (14.08)	0.5051*** (14.00)
NASDAQDummy	-0.0011 (-0.80)	0.0014 (1.01)	0.0018 (1.25)	0.0017 (1.19)
Underwriter	-0.0069*** (-5.32)	-0.0062*** (-4.71)	-0.0063*** (-4.78)	-0.0062*** (-4.77)
Toptier	0.0018 (1.55)	0.0015 (1.23)	0.0014 (1.17)	0.0014 (1.20)
Constant	0.0733*** (18.26)	0.0778*** (19.19)	0.0783*** (19.32)	0.0781*** (19.30)
N	4701	4690	4700	4699
Adjusted R ²	0.2389	0.2119	0.2113	0.2110

Underpricing is defined as $((P-OP)/P)*100$, where P is the prior offer closing price and OP is the offer price. Immediacy cost (30days), (11days), and (5days) are variables calculated based on the volume of 30 trading days, 11 trading days and 5 trading days prior to the issue respectively. Volatility is the standard deviation of daily close-to-close returns over the 30 trading days ending 11 days prior to the offer. CARPos (CARNeg) is defined as the cumulative market-adjusted return over the 5 days prior to the offer and it equals zero if the return is negative (positive), where market return is defined as the return on the CRSP value weighted index. GrossSpread is defined as a percentage of the issue proceeds. LnPrice is the logarithm of closing price prior to the offer. CLUSTER is a Dummy equal to one if the offer price is set at integer. CloseBidDiffNYSE (CloseBidDiffNas) is Closing transaction price-closing bid quote/closing transaction price and is zero if the issuer is list on Nasdaq (NYSE). NASDAQDummy is a dummy variable equal to one if the issuer is list on Nasdaq. Toptier is a dummy equal to one if the SEO underwriter (book manager) has an analyst group ranked among the top 10 groups selected by Institutional investor each October of the prior calendar year. Reloffersize is the ratio between the shares offered to the outstanding shares prior to the offer. Expected proceeds are defined as the production of closing price prior to the offer and shares offered. Underwriter is a dummy equal to one if the book manager of the syndicate has a reputation rate more than 8 in the ranking proposed by Ritter <http://bear.warrington.ufl.edu/ritter/ipodata.htm>. The value of t statistics is in brackets. ***, **, and * represent 1% 5% and 10% significance, respectively.

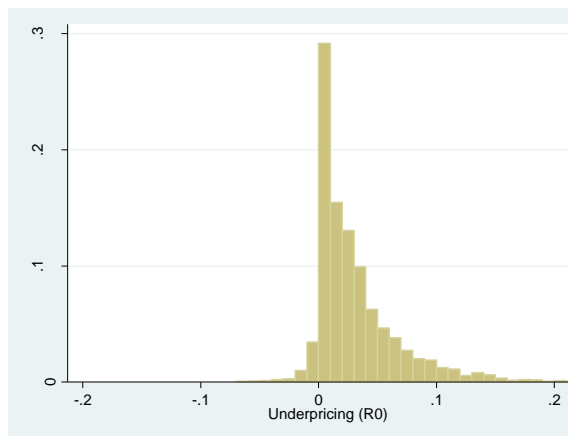
In sum, in this section, we explore the possibility of incorporating a structure model into the empirical model. However, this attempt does not generate the desired results. We attribute the failure to the difficulty of assessing the arrival rate and inaccessibility to the bid information from the book building process. Although the attempt is unsuccessfully, we find that there is no empirical evidence to prove that demand in the primary market is closely related to that in the secondary market. We also suggest that the limit order model may have a chance to be utilized by those banks with confidential bid information collected in the book building process. Unfortunately, in academic research, unless the information is available, the chance for the limit order model to be incorporated into SEO underpricing studies is slim.

Appendix 4

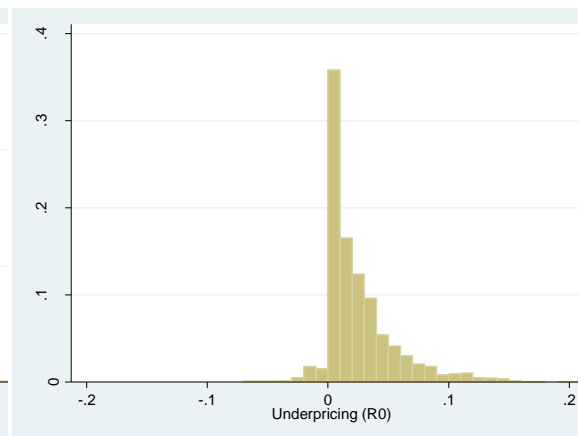
Table A-3 Descriptive statistics of underpricing R(0) and underpricing R(1) with reduced size sample

year	No. of Obs.	Mean of R(0)	Median of R(0)	Mean of R(1)	Median of R(1)
1987	85	0.0096	0.0000	0.0104	0.0074
1988	40	0.0114	0.0121	0.0154	0.0071
1989	85	0.0138	0.0109	0.0186	0.0098
1990	51	0.0213	0.0108	0.0229	0.0132
1991	167	0.0260	0.0196	0.0225	0.0130
1992	150	0.0305	0.0225	0.0305	0.0184
1993	374	0.0241	0.0129	0.0226	0.0096
1994	206	0.0227	0.0153	0.0273	0.0143
1995	341	0.0269	0.0180	0.0252	0.0135
1996	394	0.0332	0.0195	0.0337	0.0150
1997	342	0.0268	0.0175	0.0277	0.0135
1998	216	0.0217	0.0120	0.0228	0.0097
1999	256	0.0270	0.0167	0.0311	0.0131
2000	267	0.0312	0.0209	0.0458	0.0178
2001	182	0.0382	0.0258	0.0434	0.0268
2002	187	0.0332	0.0267	0.0290	0.0218
2003	217	0.0312	0.0212	0.0385	0.0206
2004	239	0.0271	0.0200	0.0283	0.0129
2005	183	0.0302	0.0208	0.0290	0.0114
2006	179	0.0314	0.0221	0.0297	0.0178
2007	152	0.0274	0.0214	0.0225	0.0074
2008	130	0.0489	0.0348	0.0436	0.0133
2009	313	0.0602	0.0492	0.0444	0.0267
Period1 1987-1995	1,499	0.0235	0.0152	0.0235	0.0116
Period2 1996-2001	1,657	0.0296	0.0190	0.0336	0.0147
Period3 2002-2009	1,600	0.0375	0.0263	0.0338	0.0171
p-value for diff(2)-(1)		0.0000	0.0000	0.0000	0.0011
p-value for diff(3)-(2)		0.0000	0.0000	0.4661	0.4351
Underpricing R(0) is defined as $((P-OP)/P)*100$, where P is the prior offer closing price and OP is the offer price. Underpricing R(1) is defined as $((P1-OP)/OP)*100$, where P1 is the closing price on the issue day and OP is the offer price. p-values for difference within subsample means (medians) are from standard t-tests (Wilcoxon rank-sum test)					

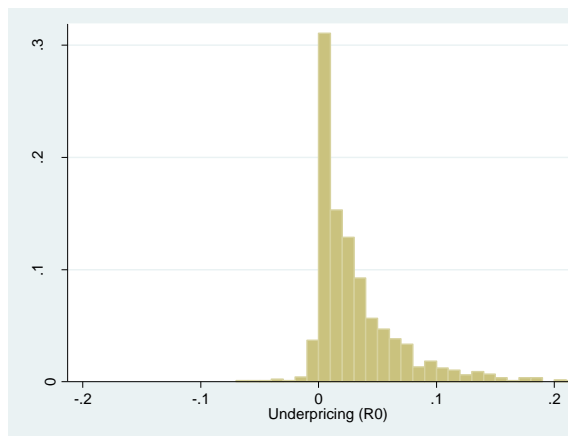
Appendix 5



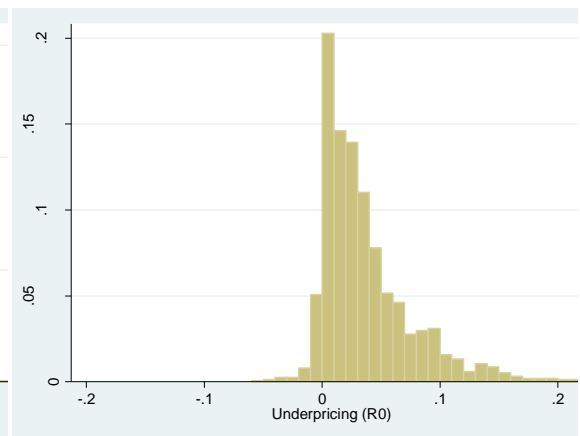
Panel A Rate of Underpricing (R0) From 1987-
2009



Panel B Rate of Underpricing (R0) From 1987-
1995



Panel C Rate of Underpricing (R0) From 1996-
2001



Panel D Rate of Underpricing (R0) From 2002-
2009

Figure A-2 Panels of magnitudes of underpricing (R0) for the reduced size sample